Modeling and Improving Patient flow at an Emergency Department in a Local Hospital Using Discrete Event Simulation

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Abstract

Like many hospitals in the US, a local hospital was experiencing patient dissatisfaction as a result of long length of stay (LOS), long waiting time, and crowded waiting room in its emergency department (ED). To help analyze its process and justify proposed changes at this ED, discrete simulation models were built using the software ProModel in this thesis. Discrete event simulations are used in many different industries for process improvement, including the health care system. This study started from literature review in both simulation and emergency medicine fields, aiming to identify best practices in both methodologies and ED practices. Then, a careful data collection and analysis was performed. Besides the large data files provided by the hospital, data were also collected through many observations of the system, interviews with staffs, and time studies to provide valid and accurate input to the simulation models. The project was completed in two phases: in phase I, a simple simulation model was built to study the impact of bottlenecks identified by the ED staffs. Experiments were conducted to show possible improvements that would be achieved if the process at the bottleneck locations could be improved. Some best practices reviewed in literature such as adding a discharge lounge was modeled to see how it could improve patient flows in the system. In phase II, more simulation models were built with a lot more details with an aim to study the impact of a proposed change to the process. . The models built in both phases were verified and validated in multiple ways. Experimentations were run and hypothesis tests were performed to confirm if the suggested changes will improve certain measurements such as the patient length of stay and patient waiting time.

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Chapter 1 Introduction

The ED in a regional hospital in Minnesota, as in many ED's the United States, continuously experiences issues with overcrowd facility, long patient waiting time and the resulted leave-without-being-seen (LWBS) of patients, especially those with behavioral health problems. To overcome this problem, it is required that health care system run as effectively and efficiently as possible. Though many different practices have been or are proposed to be implemented in the ED at the regional hospital to improve its patient flow, due to the complexity of the system, the impact on the system performance of those practices is hard to be quantified or tested. The purpose of the research in this thesis is to build a valid and effective simulation model to justify further changes and promote system improvement. Using a computer model to imitate the dynamic behavior of the ED system, changes to the system performance parameters such as patient waiting time, patient length of stay (LOS), LWBS rate, etc. can be tested in different scenarios when changes are imposed to the process. With the simulation models, team members working on process improvement in the ED can better visualize and communicate their solutions to foster better and faster decisions.

In this thesis investigation of the current process is placed and an "as-is" model is built to mimic the system behavior of the current ED process. To do this, current process of the ED is studied and need of data is analyzed. In the next step activity time at each step for each type of patients, routing decisions at each location as well as the associated possibilities, the percentages of patients in different categories, resources needed for each activity is collected and calculated based on data provided by the ED team. To get a deep understanding of the process and collect additional required data the ED staffs including a registered nurse (RN), charge nurse, and physician are followed. The “as-is” model is completed, verified, and validated. In the next step, different “to-be” models are built to test the impact of changes that the ED is currently considering as well as suggested solutions from the best practices reviewed in the literature review chapter. Parameters are defined to measure the system performance of the changed process and compare to the current process for the ED team to decide the cost-effectiveness of the changes. This thesis is organized in the following way: Chapter 2 includes the literature review, chapter 3 is the basic model and experiments on it, and chapter 4 includes the “as-is” and “to-be” models, analysis and comparison. Chapter 5 includes the future studies, limitation, and conclusion.

The emergency department of the real hospital was studied in this thesis that has 26 rooms in five different zones, red zone, blue zone, yellow zone, purple zone and fast track rooms. It has two entrances, one for a patient arriving by ambulances or police cars named EMS/LAW arrival, and one for others called Walk-in arrival. In most cases, staffing consists of 3 physicians, 6 to 14 RNs and 3 to 6 nurse assistants known as Aids with overlapping shifts. One RN stays in the triage room and one has the duty as a charge nurse who is responsible to assign nurse and physician to a patient, allocate a room to a patient, contacting incoming ambulances and manage the patient as they arrive at ED. RNs are in their own station in each zone and responsible to take care of patients at their own zone. However, in an urgent situation, with the supervision of the charge nurse, they can leave their own zone to help other nurses in the other zones. In contrast, Aids do not have any specific zone and they float between zones. One registration clerk stays in registration counter located next to the walk-in entrance to admit walk-in patients and enter their 3 identifiers into the ED information system, while another registration clerk completes registration by the bed in the rooms, especially for EMS/LAW arrival patients. A large waiting room with a capacity of approximately 30 seats for patients and family members located next to the registration desk. A designated waiting room is considered for pediatric patients in the ED. For higher level care, patients are admitted to the hospital and will be transferred to floors whenever the admission and bed assignment by the hospitalist is completed. Patients are also being transferred to other hospitals, rehabs, clinics in case. This thesis is organized by reviewing literature in simulation application in healthcare system in chapter 2, and continued with modeling in two phases in chapter 3 and chapter 4. Chapter 5 includes conclusion, limitations and future works.

Chapter 2 Literature Review

The system studied in this thesis is a multi-channel multi-line waiting system. There are many different approaches to analyze the health care systems and address its problems. Operation research is one of successful approach that provides different systematic methodologies and techniques using mathematical modeling to tackle challenges in healthcare system. Queueing models based on queue theory is one of the effective tools in improving the health care system. Many researchers and practitioners have significantly focused on queue theory to improve the health care system in recent years, responding to increasing demand at the lowest cost.

Samuel Fomundam in 2007 conducted a survey of queuing theory applications in health care system, focusing on areas of waiting time, utilization analysis, system design, and appointment systems at different levels, including departments, facilities, and regional healthcare systems [1]. Minimizing the waiting time of patients and maximizing the utilization of the system including servers and resources such as doctors, nurses, beds are conflicting objectives in a queuing system. When the demand exceeds server capacity, a patient may not wish to wait in a queue any longer and decide to omit to take the service, called reneging. Reneging as an important characteristic of healthcare helps the system to attain a "state of dysfunctional equilibrium" [2]. A proper queuing system reduces reneging through separating patients by the kind of service required. Most of queueing models is based on a constant arrival rate, although the real healthcare system has an inconstant arrival rate [3].

Appointments systems decrease the arrival variability and the time patients must wait to get the service in the system. Reduction in patient waiting time significantly reduce cost of healthcare facility. Lakshmi and Sivakumar presented a comprehensive literature review on 141 articles to determine the last updated queuing models in the health care areas. It described the trend of applications in queueing models. Half of contributions of queuing models in healthcare belongs to 2000 and after that due to development of computational ability [4]. One of the main issues in utilizing simulation is the comprehensive and detailed data are required to support such studies. Queuing theory helps researches to provide simple models required less data, fast to use while including randomness [5]. A.K Erlang firstly introduced queuing theory in 1913 applying in the telephone facilities. Beside of determining the required capacity to meet the demand, queueing models can also provide a deep insight on the level of specialization and flexibility of resources to use in the system [4]. The aim of this literature review conducted by Lakshmi and Sivakumar was to determine the leading areas of healthcare problems addressed by queueing models. They categorized the queuing models based on the most important referenced management problems in health care processes including system design, system operation, waiting time and appointments system assessment. Most of queueing theory analysis articles are found in health care management. There are three main subgroups of queueing modeling including healthcare system design, health care system operations and healthcare system analysis. In the healthcare system design, models forecast future demand and consecutively assigning required resources to the system. To prevent losing patients due to very competitive market in health care system, hospital and clinics must provide efficient patient flow and adequate resource utilization rate and maintain low staff and physician idle time.

In this regard, resource scheduling and patient scheduling in the healthcare system operation are the two main areas that affect patients. Queuing models provide information about all processes in the healthcare systems including waiting time, utilization rate, and length of stay to find the reasons of problems related to the patient care.

Review of literature was continued by searching several databases to find articles focused on the application of operation research techniques, particularly on simulation application aimed at improving the quality of service in the healthcare system.

Simulations are computer models to mimic a real-world process or system over time in order to improve and evaluate its performance to get a better result [6]. Modeling complex system has become common in many fields such as engineering, health, transportation, military, and management. since systems in these areas are complex and doing experiments has risks, simulation tool has become the method of choice because it provides an environment to do an experiment in a complex system without exposure to risk [7]. The main purpose of simulation modeling and analysis of different systems types are: [8]

- Getting insight into the operation of a system.
- Improve system performance by developing operating or resource allocation policies
- Testing new concepts before implementation
- Information acquisition without disturbing the actual system.

One of the main advantages of simulation is the ability to deal with complex real-world systems that result in providing practical feedbacks of different scenarios [9]. It helps users to assess the accuracy and efficiency of a decision. It provides an opportunity for practitioners to see the result and effect of an alternative decision on the system without applying it in the reality. Moreover, simulation modeling helps users to run experiments in a compressed time [8]. The operation and interaction of lengthy processes in the system can be simulated in a second for several times to make the analysis more reliable. Besides, most simulation software packages have the operation animating capability which helps the users to debug the model and demonstrate how the system works [8].

There are generally two approaches to simulation framework. The first approach is using simulation process to validate or tests the effectiveness of any optimizing method applied in the system. In another word, it is an analysis tool for multiple scenarios in a system. The second one is using simulation process as an optimization method to determine optimum characteristics of a complex system in order to maximize or minimize one or multiple objectives. Hence, simulation application can be summarized into answering two questions, the first approach answers what happens if. While the second one answers how do I get. According to these two approaches, the literature review is classified into two categories including validation-simulation studies and optimization-simulation studies.

There are three main techniques used in the simulation, discrete event simulation (DES), system dynamics (SD), and agent-based simulation (ABS). Among these three simulation methods, DES is the most widely used technique. It models a complex system as a series of well-defined discrete events that occur over time. DES assumes system do not change between events [10]. In contrast, SD is an approach that applied to model complex systems with the time-varying and nonlinear behavior of the system. It focuses more on flows in a system instead of the individual behavior of entities [8]. Agent-Based Simulation is a comparatively new method which models systems as being made up of self-directed agents. These agents follow a series of predefined rules to achieve objectives while interacting with each other and the environment [11]. According to the nature of healthcare system and the field of study of the thesis, this work particularly focuses on discrete event simulation.

2.1. Simulation studies (Discrete Event Simulation Based)

In recent years, discrete event simulation in health care has been applied increasingly [12]. Simulation allows health care administrators and managers to evaluate the efficiency of existing systems, to ask 'what if?' questions, and to develop and test a new system [13]. A simulation model of a system can also be applied in predicting the effect of changes in resource utilization (staff or physical capacity), resource shifts or patient flow. The result of running simulation scenarios help managers with the decision-making process regarding reconfiguration of existing systems, improving system performance, redesigning of facility and locations, and to plan a new system without the expenditure of resources.

Several studies have been conducted in the application of DES as an effective tool to improve the process in the healthcare system to minimize health care costs and increase the satisfaction of patients [13].

DES allows administrators and managers to measure the efficiency of existing health care systems, ask “what if” questions, and design new systems. Besides, DES can be applied to forecast the effects of changes in patient flow and required resources (staff or physical capacity), determine the complex relationships among the different model variables. The results help managers in their decision-making process and can be used to reconfigure existing systems, improve system performance or design, and plan new systems, without changing the current system [13].

The main problems in the healthcare system that are addressed based on OR knowledge, are scheduling, resource allocation, and patient flow problems [14]. Many studies have been conducted to optimize processes and patient flow in the healthcare systems. The optimized patient flow is defined as high patient throughput, low patient waiting times, and short length of stays while keeping the staff utilization rates high and reducing the staff idle time. Increasing cost of providing high-quality health care, made hospital administrators to minimize resources while still striving to provide the service with the desirable quality. Many studies find simulation modeling attractive since it can estimate operational characteristics of a complex system as well as monitoring the results of changes in the planning and resource allocation prior to implementation, which minimize the financial risks for decision makers. According to the field of study of this thesis, the literature review of DES in validation-simulation studies is classified into two categories including patient flow and resource allocation.

2.1.1. Patient flow

Three areas influence on patient flow in a healthcare system, including patient scheduling and admissions, scheduling of resources; and patient routing and flow schemes [13]. Scheduling and admissions focus on patient appointments scheduling procedures to determine how and when patients are admitted on a certain day, and how long each appointment is going to be, and how much the buffer time between appointments should be. Proper allocation of resources maximizes the patient flow while minimizing the associated cost. Optimum patient routing and flow minimize patient waiting time and increase staff utilization rates.

Fetter and Thompson applied one of the earliest applications of simulation in healthcare [15]. In this study, authors calculated the physician utilization rate and patient waiting time according to input variables including patient load, patient arrival patterns, appointment intervals, no-show rates, walk-in rates, service times, interruption times, and physician breaks. The results showed that if the capacity of the outpatient clinic (physician appointments) increases from 60% to 90%, the physician idle time can be decreased by 160 hours. However, this will result in increasing the patient waiting time by 1600 hours (over a period of 50 days).

Smith and Warner compared two scenarios in terms of different patient arrival patterns in a clinic [16]. In the first scenario, they considered uniform arrival patterns for patient arrival while the second scenario had highly variable patterns. Results showed that the scenario with uniform arrival patterns can reduce the average length of stay from 40 minutes to 24 minutes.

Rising et al. analyzed the daily arrival pattern of patients to schedule more appointments when the demand of walk-in patients is low [17]. A Monte Carlo simulation model showed that patient throughput can is increased by 13.4% and clinic over-time is decreased through smoothening the overall daily arrival.

Evans and Unger simulated the flow of 13 different types of patients to evaluate the performance of various feasible schedules for nurses, technicians, and doctors, finding the optimum schedule with the minimum average length of stay of patients in the emergency department [17].

Giachetti et al. addressed three different problems that are commonly experienced by outpatient clinics such as long patient waiting times, high no-show rates, and large appointment backlogs [18]. A new scheduling approach is proposed to solve these problems. They developed a discrete event simulation model to improve patient throughput time. in order to find factors leading to a high no-show rate a system dynamic simulation model is used. Their study identified strategies that clinic management can use to improve patient throughput time by 50%.

Ruohonen et al. developed a simulation model to demonstrate a new operational method named Triage Team to make the operation of the emergency department more effective [19]. Triage Team consists of specialized nurses who identify the urgency of patients' issues through taking basic tests and interviewing them. The proposed model suggests the Triage Team starts its procedures when patients arrive and the registration process is completed. The results of the simulation showed that proper implementation of the proposed method can result in over 25% improvement in patient flow.

Kolker developed a simulation model to represent daily processes in the ED [20]. He found that LOS is meaningfully larger for patients who are discharged from the ED and sent to a hospital rather than those who are discharged to go home. This study certainly supports the hypothesis that improving patient flow in the hospital positively affects the patient flow in the ED.

Regarding patient flow improvement in an outpatient clinic, Chand et al. considered three sources of variability and improvement factors [21]. Variabilities are divided into four components: patient arrival pattern, registration time, departure time from registration to the waiting room, and time with physicians. This study demonstrated that identifying the sources and mitigating the undesirable effects of variability at different stages significantly improve the patient flow in the system. They applied simulation to evaluate the effects of improvement factors on the system performance. The outcome showed that the outpatient clinic can serve 37% more patients by optimizing the appointment system which consecutively improves the patient flow in the system.

2.1.2. Resource allocation

The reviewed articles have different approaches regarding the allocation of resources. Therefore they are divided into three sections of (1) Bed sizing, (2) Room sizing, (3) Planning and staff sizing [13].

2.1.2.1. Bed Sizing

Simulation is the most common methodology applied in the emergency department to overcome bed shortage through trading off between utilization rates of bed occupancy and number of patients served. Simulation offers the precious "what-if" tool for administrators and managers in the health care system to determine the number of beds required for each unit while profitability is maintained. It helps to experiment different bed allocation scenarios to optimally utilize of health care facilities. Dumas developed a simulation model to assess different bed allocation scenarios and find the best-case reallocation [22]. The author used three different measures to evaluate the model and compare it to the actual data. Results showed 115 more patients can be served through the proposed reallocation model in a year. Lowery studied the application of simulation modeling in the ED to help administrators in determining the number of required beds to meet the demand [23]. The simulation model's predictions are compared with the actual hospital performance, and it showed improvement in all nine units of the ED in a four-year period. A new two-phase approach presented by Butler to determine the optimum facility layout and allocation of resources at a hospital [24]. The first phase includes integer programming to specify layout and bed allocation. In the second phase, simulation is applied to evaluate the performance of the system in terms of patient waiting time reduction. It is found out that changes in the outside of the ED can improve the ED performance consecutively. For instance, adding 20 beds (43%) in one ICU resulted in about 10% reduction in LOS for admitted patients in the ED [25].

Montgomery developed a discrete event simulation model to consider variations in a healthcare system, using probability distributions to determine patient distributions and its flow in the system [25]. Several scenarios are examined to analyze the impact of closing or opening beds and changing the patient flow policy on the output variables of the daily census and the percentage of beds filled. Results showed leaders how their decisions might impact the whole system.

Landa et al. used simulation to evaluate the outcome of different bed management policies in a local hospital based on a set of performance indexes, considered from the hospital point of view (bed occupancy, turnover interval, additional beds) and the patient point of view (misallocation, cancellations of elective admissions are already scheduled, excessive waits) [26]. Moreover, they defined five performance metrics such as; misallocation, an average number of patients waiting for admission, the number of elective patients postponed due to unavailability of beds, bed utilization rate, and waiting time for emergent patients from the admission to inpatient wards. Six different scenarios tested by the verified model to find the best one that improves the system performance without increasing the bed capacity.

2.1.2.2. Room sizing

Simulation modeling can be used for experimenting integration or construction of new facilities and departments to find the most cost-effective decision to meet the demand. The number of rooms and its size considered as one of the critical resources to keep the system profitability and serve patients efficiently. Currie et al. developed a new simulation model of a hospital to estimate the number of required bed and operation rooms in case of facing a 20% increase in demand [27]. Different scheduling plans are experimented through simulation modeling of an operation and recovery room by Kuzdrall et al. to assess and determine the proper utilization of facility needed [28]. Results showed that proper scheduling of the current facilities can reduce the costs and increase the number of patients served. Olson and Dux stimulated the expansion of an operating room in a hospital to predict whether the hospital can handle hospital's demand for two years or not [29]. Results proved that separating inpatient and outpatient procedures would be a better decision to meet the increased demand of hospital in future. Besides, Meier et al developed a simulation model of a hospital, examining eleven different scenarios to find a number of required operating rooms for next five years [30]. Mahachek and Knabe tested the scenario of reallocating rooms to two different units in a hospital to reduce costs [31]. The simulation result showed the average patient waiting time in total is increased due to lack of the required examination room, although such decision can reduce the costs. M.J. Cote described the results of a discrete simulation model of an outpatient clinic to demonstrate the relationship between examining room capacity and patient flow by using four clinic-based performance measures [32]. In this study, the author stated that patient waiting time wouldn't certainly get longer when resource utilization is increased.

2.1.2.3. Staff sizing

Staff sizing and its distribution among departments in a healthcare system have a significant impact on reducing patient waiting time and increasing patient throughput. Moreover, staff scheduling and allocation of resources in ED affect the quality of service. Several studies have been reviewed to understand the application of simulation as an effective tool to test different staffing scenarios in a health care system and determine staff size in each department. A linear optimization model is proposed by Sinreich and Jabali to find a resource's contribution to ED operations [33]. The results showed that adding a doctor and nurse in the regular working hours' shift results in patient waiting time reduction while maintaining staffing levels. Sinreich et al. proposed two heuristic algorithms to provide efficient work schedules for the ED staffs which reduced patient waiting time between 20% and 64% and patient LOS between 7% and 29% [34].

Paul et al. stated that overcrowding of the ED is one of the main problems in the hospital [35]. The suggested improvement plans are examined through the DES approach. The outcomes are compared with the primary performance of the system. The results showed that adding a physician to peak hours decreases patient length of stay by 18%.

Gul and Guneri applied DES to model an emergency department unit that faced long patient length of stay [36]. The system is analyzed according to different scenarios of resources allocation to determine the upper and lower bounds of the number of human resources. Afterward, all configurations are examined to find the optimum one, resulting in the minimum length of stay. In the suggested scenarios, shift hours are changed and the number of doctors and nurses worked in the evening shift are increased one for each. The results showed 30% reduction of patient average waiting time as well as 12.5% improvement in patient throughput. Besides, a scenario is tested in the case of an increase in patient demand in the future as a decision-support tool for hospital administrators.

Wang et al. suggested three scenarios to tackle ED overcrowding and long patient LOS [36]. New nurse schedule, combining registration with triage process, and adding one float nurse working in the evening shift are experimented through simulation modeling. All the scenarios are tested with the assumption of mandatory requirement of first physician's evaluation within 30 min since bed assignment. The result showed 24% reduction in the LOS by applying a new nurse schedule, 5% reduction in the LOS by combining triage and registration processes, and about 28% reduction in the LOS by adding one float nurse working from 4 P.M to 12 A.M.

Weerawat et al. simulated the orthopedic outpatient department ward in a large hospital [36]. Key performance indicators (KPIs) are defined to measure effects across several clinical operations throughout different shifts of the day. The staff size with a new schedule is suggested to meet the demand in future considering increasing trend of patient visits. The authors also mentioned that the designed simulation model can be used in other words by changing parameters such as processing time, the proportion of patient types, and numbers of staffs. Impacts of increasing demand on service performance through testing different simulation scenarios are also discussed.

Rohleder et al. applied discrete-event simulation modeling to support process improvements at an orthopedic outpatient clinic [37]. The simulation modeling helped them to identify optimum staffing levels and better patient scheduling. The result shows that waiting time is significantly improved and overall patient time in the clinic is reduced. The length of initial waiting time, total patient clinic time, X-ray waiting time and waiting time for surgeon are reduced by 61%, 33%, 69%, and 35% respectively.

2.2. Optimization- Simulation Studies

Operations research is a methodology that applies advanced mathematical modeling and analysis to help practitioners to make decisions for a complex system such as healthcare. DES is one of the most common operations research tool applied in healthcare systems due to its unique ability to deal with complexity and variability of the real world. However, it also has some limitations to deal with a complex system which has many stochastic input decision variables and there is a lack of information about the structure of output function. In such situations, optimization methods are applied along with simulation to maximize or minimize measures of the performance by evaluating the system using discrete event simulation. The optimization model is a mathematical model/equation, where simulation input parameters are defined as the independent variables and response or outcomes of the simulation are considered as dependent variables. Most of the today's simulation software includes an optimization package which can solve such equation [38].

Smith-Daniels et al. applied simulation in healthcare by combining it with optimization methodology to get better results. Research efforts prior to 1980's are failed due to lack of balance between objectives of all healthcare professionals[39].

Harper demonstrated that simple deterministic spreadsheet calculation cannot provide the precise forecast of bed size requirement. However, a simulation model would provide a better forecast of the number of beds required. This study also indicated that combination of simulation models with optimization techniques would help hospital administrator to optimize the system processes [40]. Zhang et al. integrated DES with optimization techniques to analyze the long-term care capacity planning. Several operation research and statistical methods are combined to determine LOS variation by age, gender, and geographic region [41].

Miller et al. discussed how the combination of simulation, linear programming, and spreadsheet analysis would help to find the optimum allocation and tasks scheduling in the healthcare system. The presented model balanced the tradeoff between space utilization and profitability [42].

Yeh applied simulation and the genetic algorithm (GA) to reschedule the nurses' shifts to improve the quality of service at ED. Simulation is applied to model the patient flow in

ED while GA is applied to find a near-optimal solution for nurse scheduling, minimizing patients' waiting time. The computational results showed that average waiting time for patients in the queue is reduced by 43% [43].

Ahmed et al. integrated simulation with optimization technique to design a decision support tool for operations of an ED unit at a hospital to determine the optimal number of doctors, lab technicians and nurses required to maximize patient throughput and minimize waiting time, subject to budget restriction. The result showed 28% increase in patient throughput and an average of 40% reduction in patient waiting time. Besides, the presented simulation model can be applied as a decision supporting system to evaluate the impact of different staffing levels on service efficiency [44].

Abbas Al-Refaie et al. proposed a cellular service system to develop ten nurse assignment configurations in the ED. Simulation is applied to find the best scenario based on performance measurement of each configuration. The result showed 10% reduction of patients average waiting time, increasing number of 80 patients served in one month and improving the nurses' utilization from 52% to 62% [45].

Banditori et al. presented a mixed integer programming model to maximize the patient throughput in a surgical center, considering the cases' due dates and control of the waiting list [46]. A simulation model is applied to test the model solution's robustness against the fluctuation of surgery duration and the length of stay. According to the two presented models, an integrated optimization-simulation approach is developed to trade-off robustness and efficiency.

Holm et al. stated that deterministic methods are inadequate for improving patient flow processes due to stochasticity characteristic of the system and complexities. The authors studied a case of a hospital where some wards had high utilization rate while others had a lower occupancy rate [47]. The optimization method is integrated with simulation modeling to develop a DES model of patient flow in the hospital wards, where each ward has its own probability distribution for arrival time and LOS. The model is applied in order to reallocate the hospital beds to the ward with high occupancy rate. Results showed that the novel allocation algorithm minimizes hospital overcrowding by 2% [47].

Wang et al. described how the multi-objective discrete optimization via simulation framework can be applied to identify process improvement opportunities in a large hospital. Three control factors of a simulation model including bed allocation among wards, overflow threshold, and discharge distribution are evaluated and individually optimized with aim of minimizing overflow rate and patient waiting time[48].

Azadeh et al. present an integrated simulation and data envelopment analysis (DEA) approach to increase the quality of service in a neurosurgical intensive care unit (ICU). Simulation modeling is developed and run for different scenarios generated to observe the effects of various parameters such as lengthening or shortening treatment times, decreasing or increasing patient volumes and removing or adding staff members on the system performance. The DEA is applied to compare the outputs of different scenarios[49].

Yi et al. developed a novel simulation model to demonstrate the operations of a hospital faces a natural disaster situation like an earthquake [50]. Generalized regression equations are fitted to the simulation model results to get steady-state hospital capacities. In order to predict the transient capacity of multiple hospitals in the disaster situation in a timely manner, a parametric metamodel is developed. A new framework is presented by Eskandari et al. to investigate the patient flow of the ED. They proposed AHP and TOPSIS decision models to evaluate and rank outcome of the simulation model. The results indicated a reduction of average waiting time for the patients [51].

2.3. Practices Applied in the Emergency Department

The ED visit rate has been greatly increased in last two decades. ED overcrowding has become a public health problem resulting in long patient waiting times and delays in critical treatments [52]. In the United States, EDs are the gate to hospitals where 50% of admissions occur [53]. The improvement actions in ED, which may not be applicable elsewhere in health care system, positively affects the whole system performance. Improvements in ED influences on the U.S health care expenses since one-third of the U.S health care bill come from admitted patients [53].

In this section, studies are reviewed that focused on ED crowding's effect on prolonged patient waiting times, patient and staff dissatisfaction and high rate of left without being seen (LWBS) in the system. Novel practices are suggested to improve patient flow which is classified into three categories: patient arrival schemes, practices within the ED, and patient release schemes[54]. These practices were reviewed to be suggested and tested through simulation modeling in chapter 3.

2.3.1. Patient Arrival Schemes

In this domain, studies are focused on patient flow improvement at the arrival, particularly on ambulances where the patient arrival can be controlled.

Ambulance deployment and location— the response time of ambulances can be used as a key performance metric to evaluate prehospital emergency medical services (EMS) since deducting minutes off can save lives [55]. Peleg and Pliskin presented a simulation model of geographic information system (GIS) that can respond to 94% of the calls within 8 minutes [55]. Rajagopalan et al. developed a search algorithm that improves EMS system performance through the dynamic deployment of ambulance addressing fluctuation of demand throughout the week [56]. Gendrau et al. developed a novel integer linear model for a dynamic relocation problem of ambulances to meet an acceptable demand and control the number of relocations simultaneously [57]. Simulation results showed the benefits of relocating ambulances in the reducing average response time.

Ambulance diversion—Ambulance diversion (AD) is a flow management technique firstly reported in the 1990s and recently being more applied due to the ED overcrowding. AD goal is to reduce the arrival rates by redirect incoming EMS to neighboring hospitals. An accurate implementation and execution of AD benefit hospitals by resource pooling and reducing overcrowding in the EDs [58].The effect of the AD on the system varies by type of diversion and community characteristic.

2.3.2. Practices within the ED

General triage interventions—Triage is a technique to classify patients based on their acuity level. In the U.S, the triage is based on the five-level Emergency Severity Index (ESI) proposed by Wuerz et al. which combines urgency of care with an estimate of required resources [59]. Wang indicated that a five-level scale is better than a three-level scale since a queueing system that classifies patients into more classes which result in a more accurate outcome [60]. In a traditional system, a nurse does an evaluation of the patient in a triage room, however, it is found that assigning a physician to triage can reduce the LOS and LWBS [61]. Russ et al. studied an ED for the 23-months period and showed order placement by a triage physician reduced 37 minutes of the average time spent in an ED bed for a patient [61].

Complexity-augmented triage—According to increasing attention to triage in the ED, traditional system of triage process is shifted to the modern one. For instance, from a queueing perspective, measuring patient required service time can help prioritizing patients by using prioritization algorithms such as shortest processing time first (as it is applied in manufacturing). Saghafian et al. proposed a complexity-augmented triage. While an additional complexity evaluation at triage would take longer time, its benefit in reduction of the LOS could be noteworthy [62]. A simulation analysis validated by hospital data presented to test several queueing models to demonstrate that complexity-augmented triage improves ED performance in terms of operational efficiency [62].

Patient streaming— King et al. applied lean thinking into the health care system by applying patient streaming in the ED. The study argued rearranging patient flow in the ED based on whether a patient will be admitted to a hospital or discharged to home. The results showed that implementation of patient streaming increases the triage time due to the extra evaluation, however, overall time spent for all groups of the patient is significantly reduced [63]. Saghafian et al. proposed a combination of queuing-based analysis and simulation model to determine how disposition-based patient streaming should be implemented to positively affect ED performance. They suggested that ED resources can be shared across paths rather than physically separated [64]. Besides, patient streaming can be more effective to the EDs with (1) high rate of admitted patients (2) longer service times for admitted patients than discharged patients (3) high physician utilization and (4) long patients waiting time to be admitted to hospital. Saghafian et al. also discussed that newly admitted patients should have a higher priority to be visited by a physician to take full benefits of patient streaming, while for discharged patients, a new patient should have lower priority to be visited by a physician [64].

ED fast track—Fast track in the ED is a practice which is basically combined with triage to direct lower acuity patients into the assigned location with dedicated resources to process more quickly. Implementing fast-track lane in the ED can greatly address the overcrowding problem since approximately 80% of ED visits are non-urgent [65]. Samaha experimented the adding fast-track center, staffed by a dedicated nurse practitioner for lower acuity patient. Results showed that LOS is reduced by 24%. Afterward, a fast-track lane for lower acuity patients in the ED is implemented for the 12-weeks period that results in a reduction of the average waiting time for discharged patients by 20% [66]. Konrad tested the split-flow concept which is similar to fast track. The patients flow is split into different paths and have parallel processing based on the patient acuity level. Results showed a 48-minute reduction in an average of LOS and also a 27-minute reduction in an average of the door to doctor time [67].

2.3.3. Patient Release Schemes

Among limited studies in improving patient flow through discharge, there are two main practices including discharge lounge and reverse triage.

Discharge Lounge— Optimizing patient discharge rate has a significant impact on improving patient flow like another aspect of operations in the ED. Several improvement models of inpatient discharge time are developed to improve the ED boarding. Vermeulen et al. discussed that reducing roomed-to-discharge time in the ED is crucial for lowering LOS [68]. Williams proposed the use of discharge lounge for patients who are being discharged to wait for their prescriptions filled, receive care education, wait for transportation, or schedule their next appointments. Using discharge lounge frees up bed for incoming patients[69]. Geer and Smith suggested the implementation of a discharge room as a process improvement, resulting in a reduction of LOS time by 79% [70]. Moskop et al. introduced a "reverse triage" system for early discharge of hospital inpatients [71]. Peck et al. used a generalized linear regression model as one of a few ways to accurately predict inpatient admissions number based on the information gathered at ED triage [72].

Reverse Triage— The reverse triage practice is firstly proposed by Kelen [73]. Reverse triage idea is to safe early discharge patients in case of sudden increase in patient volume. Moskop et al. suggested "reverse triage" by developing a disposition classification system with a five-categories scale that classifies inpatient based on the risk tolerance for immediate discharge [71]. Kravet et al. considered a similar approach to demonstrate early discharging inpatient eventually reduce ED overcrowding[74].

2.4. Summery

Reduction in the LOS and average patients waiting time significantly improve patient flow and consecutively increase the number of patients served. When the patient flow cannot be controlled, resource allocation strategies play a key role to deal with variability in the system. According to the literature review, simulation modeling of a unique environment helps the healthcare system to balance the tradeoff between resource utilization and LOS. Simulation is a valuable tool to experiment different scenarios, determining an optimum number of rooms, beds, and staff to meet the demand, aimed improving patient flow and profitability simultaneously. Another way of applying simulation to the healthcare system is combining it with optimization algorithms. This approach can be used when enough confidence in the simulation modeling achieved. Before applying optimization tool to the simulation model, output of the model should be analyzed with analysts. Some examples are scheduling of patients and or physicians and nurses. Besides, it should be applied in a system when a lot of parameters needs to be changed together, other than that, simulation by itself can answer simpler what-if questions. Optimization output can be used as the simulation input to bring confident do decision makers by running experiments. Reviewing studies in the literature shows in many studies there are some level of detail missing, so in this thesis the goal was set to make a valid model with as much as detail that can be included during the time of study. Almost all the detail that can impact the parameters such as patient flow and patient waiting time were modeled. In the last part of literature review some of the best practices applied or suggested in recent studies were reviewed. Reviewing these studies helped to suggest best practices to hospital administrators after finishing the model to find if there is any of them applicable to the current system. Later the chosen one were modeled to see the impact of it on the system.

Chapter 3 Phase I- Basic Model

One of the most difficult and time-consuming tasks in simulation modeling and analysis is to obtain sufficient understanding of the system to develop an appropriate conceptual and logical simulation model. The simulation modeling approach in this study begins with developing a basic "as-is" model to represent the system activities from a high level. The level of detail for the basic model is determined based on the experiments desired by the hospital managers. The known bottlenecks identified by the ED personnel are include the hospital that causes a long turnover time (door-to-bed time) for patients that need to be admitted and transferred and the treatment location for behavioral health (BH) crisis patients that cause a long roomed-to-disposition of these patients in the ED. Due to the beds in the hospital not being available in time for the ED patients, many of the admitted and transferred patients have to wait in their ED rooms for a long time after they are dispositioned. Since the rooms for BH patients are limited and they usually have long disposition-to-depart time, they are bottleneck in the system and cause delay in the system. the basic model focuses on testing the impact on the overall patient flow to see if these two bottlenecks can be removed.

3.1. Data collection

Gaining a good understanding of the process and activities in the ED is essential to the success of the project. The data collection started with several meetings with the senior physicians and nurses of the ED to learn the procedures performed routinely by the ED staffs. During these meetings, process flow diagrams were provided and went over. Then data were collected in multiple ways including observation of the real system, a series of discussion with senior physicians, managers, and nurses, and data files provided by the hospital's IT team. Observation of the actual system provided a good understanding of the current operations and activities in details. Several days were spent in the ED to follow physicians and nurses on duty in the ED to gather data on the process as well as time and motion studies. The configuration of the ED allowed one observer to record the time while tracking patient's interactions from the registration desk, getting triaged in the triage room and directed to one of the patient care rooms. The sequence of patient's interaction with the ED staff as well as the duration of each interaction was recorded. The main purpose of the time study is to get information on real times for each process such as registration, triage time, nurse assessments time, and evaluation of physician time, follow up treatment by the nurse or physician time, discharge time, and waiting time for imaging or lab purposes. Therefore, required data about routing decisions at each location as well as the associated possibilities, the percentages of patients in different categories and resources needed for each activity were collected by the ED team.

To form distributions that can be used to generate time for each individual activity, a sample of 6908 patient records in a two-month period from Oct 15^{th,} 2016 till Dec 15^{th,} 2016 was provided by the hospital. Data were exported from the hospital patients historical computerized information system in the format of an Excel file. The raw data file includes patient information such as patient ID number, age, arrival type, patient acuity level, chief complaint and diagnosis results as well as activities time and date such as registration, triage, admission, and discharge. To make the provided data working for this work, the data cleaning was started to export the required data for simulation purposes.

3.2. Data cleaning

As mentioned earlier, raw data of patient records were provided by the hospital upon request for this work. Data includes many information and time stamps, from patient entering the ED till discharge, but not all of them were used for simulation purposes. Besides that, since all data were recorded by the ED staffs in the information system, it includes missing records and inaccurate information. Therefore, data cleaning was required to trim data and make it ready for the data analysis. Data cleaning was done in three steps:

1. Deleting the missing and inaccurate records

Since the exported data were presented to us in an MS Excel format, some functions were applied to clean the data from missing and inaccurate records. Filtering function was applied to find all the blank cells in the required columns of data and the record of all patients with missing data are entirely deleted. This process was repeated to clean all incomplete patient records from the data file. For example, for some EMS arrival patient, ESI levels were not entered by the triage nurse since the triage process happened in the room instead of triage room. And probably the nurse forgot to enter the data into the system. However, for some purposes such as finding patient arrival pattern and finding a total number of a patient visiting the ED, all records, including those with missing data were used since those missing data do not affect the result of data analysis. Figure 3-1 shows an example of cleaning missing records in cell B950, K951, and L951. The entire records of patients in rows 950 and 951 are deleted for analyzing arrival type and acuity level of patient purpose.

	A	B	C	D	E	J	K	L	M
1	MRN	Arrival Method	Arrival Method	Age at Visit	Trimmed	Age group	Acuity	Acuity	CC
944		Car	#N/A	51 year old	51 year old	7	Level 3	3	Chest Pain
945		Car	#N/A	35 year old	35 year old	5	Level 3	3	Vaginal Bleeding
946		Car	#N/A	18 year old	18 year old	3	Level 3	3	Chest Pain
947		Bus	#N/A	41 year old	41 year old	6	Level 3	3	Vomiting
948		Ambulance	#N/A	49 year old	49 year old	6	Level 3	3	Chest Pain
949		Ambulance, Go	#N/A	90 year old	90 year old	10	Level 3	3	Altered Loc
950			#N/A	63 year old	63 year old	8	Level 3	3	Chest Pain
951		Ambulance, Go	#N/A	58 year old	58 year old	7			Altered Loc
952		Ambulance	#N/A	85 year old	85 year old	10	Level 3	3	Dizziness

Figure 3-1 Data file with missing records

2. Adding index values for patients in certain categories

In the ED, each type of patient may receive a different type of care, have different routing, and get a priority to receive a care. Therefore, each type of patient should be separated and treated differently in the model as well. In the simulation model, each patient has different attributes which distinguish it from the others. By assigning attributes to the patient different routing policies and different sequence of the process can be applied to the patients. In order to assign these index values accurately, it was required to use the actual data. for this purpose, records of patient's age group, acuity level, disposition type and arrival type are selected and cleaned.

Since the ED allocate two different waiting areas to separate adults from pediatrics, it is needed to find the percentage of each to implement in the model. In the data file records of patient age was followed by "year old" or "month old". To change it to the number format for data analysis purposes, several MS Excel functions were used. In the first step, the TRIM function was used to delete any possible extra spaces entered in each cell at the end. Column E of Figure 3-2 is showing the TRIM function used. Column F of the same Figure 3-2 is showing the LEN function applied to return the length of the string in each cell, where in Column G the LEFT function was used to return 3 characters from the left side of the text in each cell and it multiplied by 1 to change it to a number. In column, I of Figure 3-2, IF and RIGHT functions were combined to check if the age was followed by "year old" or not. The IF function returns False if the record is followed by "year old" which means that patient is not an infant. In the last step in column J, IF function was used to classify patients into 11 groups based on their age, by checking the content of column H and column I. 0 to 1-year-old patients were considered as group 1, 1 to 10 years old patients as group 2, 11 to 20 years old patients as group 3 and so on. Formulas were copied all the way down for the entire records.

1	D	E	F	G	H	I	J
2–5	Age at Visit	Trimmed	Length of Column E String	3 Characters from Left side of Column E	Age in Number Format	Infant	Age group
6	42 year old	42 year old	11	42	42	FALSE	6
7	32 year old	32 year old	11	32	32	FALSE	5
8	25 year old	25 year old	11	25	25	FALSE	4
9	34 year old	34 year old	11	34	34	FALSE	5
10	37 year old	37 year old	11	37	37	FALSE	5
11	56 year old	56 year old	11	56	56	FALSE	7
12	48 year old	48 year old	11	48	48	FALSE	6
13	37 year old	37 year old	11	37	37	FALSE	5
14	94 year old	94 year old	11	94	94	FALSE	11

Key Cell Formulas

Row	Cell	Formula
17	E6	=TRIM(D6)
18	F6	=LEN(E6)
19	G6	=LEFT(E6,2)
20	H6	=1*G6
21	I6	=IF(AND(RIGHT(E6,8)<>"year old",H6>12),1,IF(AND(RIGHT(E6,8)<>"year old",H6<12),0))
22–24	J6	=IF(I6=FALSE,IFS(AND(H6>0,H6<=1),1,AND(H6>1,H6<=10),2,AND(H6>10,H6<=20),3,AND(H6>20, H6<=30),4,AND(H6>30,H6<=40),5,AND(H6>40,H6<=50),6,AND(H6>50,H6<=60),7,AND(H6>60,H6 <=70),8,AND(H6>70,H6<=80),9,AND(H6>80,H6<=90),10,AND(H6>90,H6<=110),11),1)

Figure 3-2 Adding index value for age group

A similar procedure was taken to extract a proper format of acuity level records for data analysis purpose. Figure 3-3 shows patient records of acuity level in column K and the RIGHT function which is used to change the format of records in column L. The formula was copied all the way down in this column L.

Figure 3-3 Adding index value for acuity level

To easily categorize patients based on their disposition type in the data analysis part, the records of disposition type were coded as follow: 1 for discharged, 2 for admitted, 3 for left without being seen and 4 for transferred patients. Figure 3-4 shows how an IFS function is applied in column P.

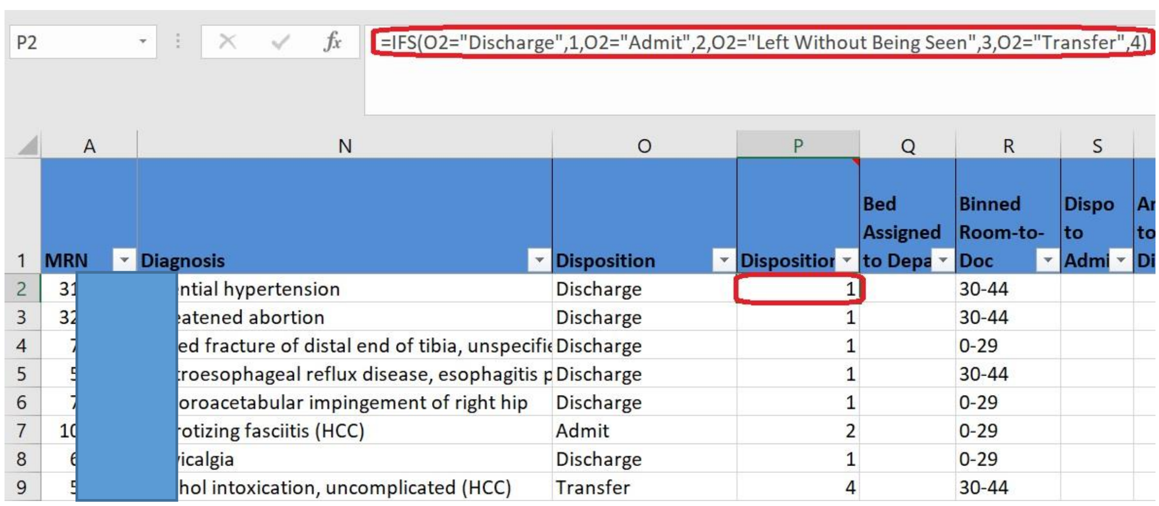


Figure 3-4 Adding index value for disposition type

The ED has two arrival points and patients arriving at each location follow a different sequence of activities. In order to analyze the data of patient arrival, an index value was added to the patient records representing their arrival type. Arrival type was divided into three main group: walk-in patients, EMS arrivals, and LAW arrivals. VLOOKUP function was applied to convert the arrival type records into the 3 arrival types: 1 representing EMS arrivals, 2 for LAW arrivals and 3 for walk-in patients. The function and the output of using the function in column C represented in Figure 3-5.

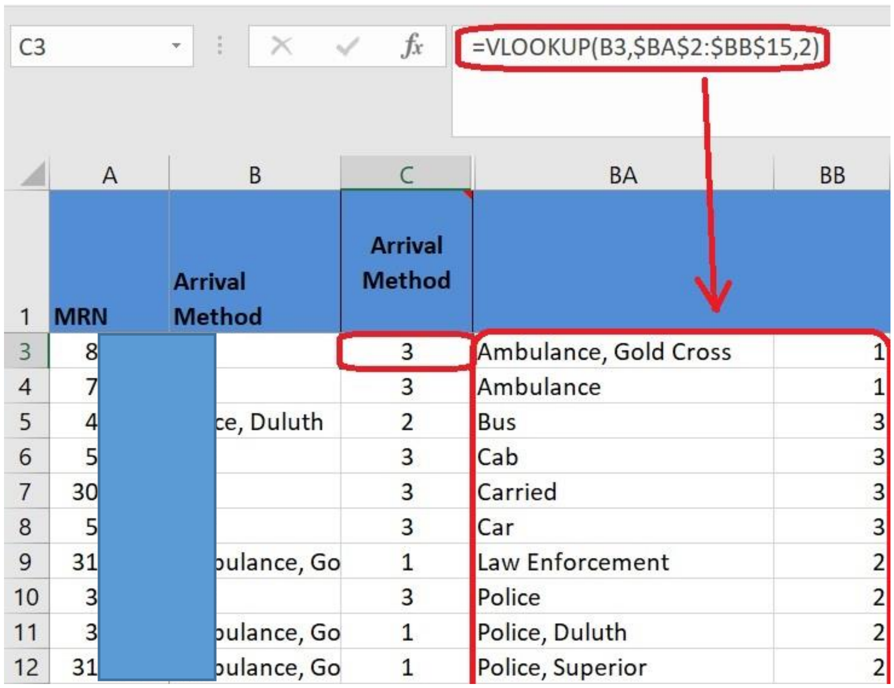
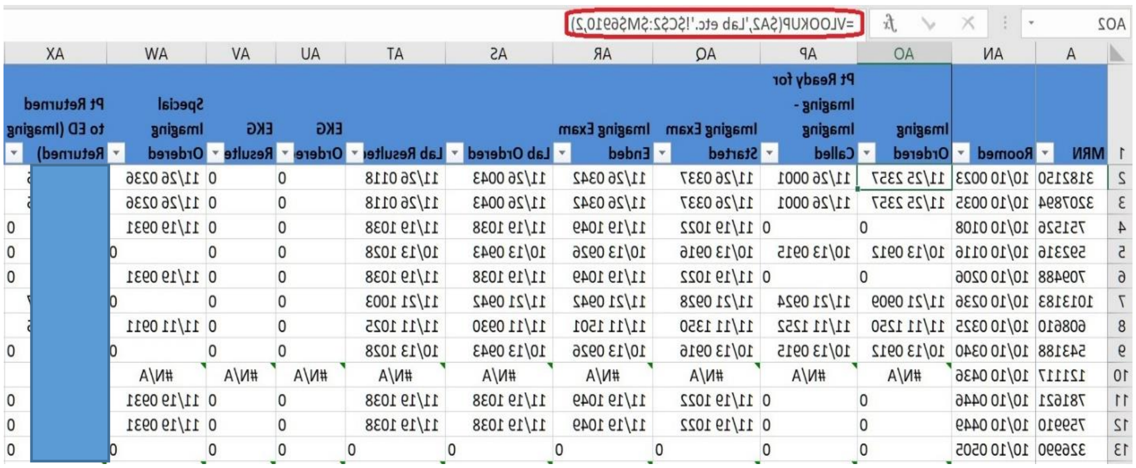


Figure 3-5 Adding index value for arrival method

3. Matching patient records from multiple sources

Since the data file was provided in different spreadsheets it was needed to aggregate all records into one sheet for the data analysis. The VLOOKUP function was applied to match patient records from different sheets by the identification number (MRN) and aggregate all into one sheet. Figure 3-6 shows how the function was used to transfer all data from a different sheet. Column AO to AX represents the lab and imaging data transferred from different spreadsheets into one may shift. For example, in column AO the imaging ordered time from different spreadsheet was copied by matching the MRN number.



AO2 =VLOOKUP($A2,'Lab etc.'!$C$2:$M$6910,2)

	A	AN	AO	AP	AQ	AR	AS	AT	AU	AV	AW	AX
1	MRN	Roomed	Imaging Ordered	Pt Ready for Imaging - Imaging Called	Imaging Exam Started	Imaging Exam Ended	Lab Ordered	Lab Resulte	EKG Ordere	EKG Resulte	Special Imaging Ordered	Pt Returned to ED (Imaging Returned)
2	3182150	10/10 0023	11/25 2357	11/26 0001	11/26 0337	11/26 0342	11/26 0043	11/26 0118	0	0	11/26 0236	5
3	3207894	10/10 0035	11/25 2357	11/26 0001	11/26 0337	11/26 0342	11/26 0043	11/26 0118	0	0	11/26 0236	5
4	751526	10/10 0108	0	0	11/19 1022	11/19 1049	11/19 1038	11/19 1038	0	0	11/19 0931	0
5	592316	10/10 0116	10/13 0912	10/13 0915	10/13 0916	10/13 0926	10/13 0943	10/13 1028	0	0	0	0
6	709488	10/10 0206	0	0	11/19 1022	11/19 1049	11/19 1038	11/19 1038	0	0	11/19 0931	0
7	1013183	10/10 0236	11/21 0909	11/21 0924	11/21 0928	11/21 0942	11/21 0942	11/21 1003	0	0	0	7
8	608610	10/10 0325	11/11 1250	11/11 1252	11/11 1350	11/11 1501	11/11 0930	11/11 1025	0	0	11/11 0911	5
9	543188	10/10 0340	10/13 0912	10/13 0915	10/13 0916	10/13 0926	10/13 0943	10/13 1028	0	0	0	0
10	121117	10/10 0436	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	
11	781621	10/10 0446	0	0	11/19 1022	11/19 1049	11/19 1038	11/19 1038	0	0	11/19 0931	0
12	759910	10/10 0449	0	0	11/19 1022	11/19 1049	11/19 1038	11/19 1038	0	0	11/19 0931	0
13	326990	10/10 0505	0	0	0	0	0	0	0	0	0	0

Figure 3-6 Matching data from different sources

3.3. Data analysis

Data analysis comes after data cleaning. Based on modeling purposes, data analysis was done on 4 different aspects, including patient classification, acuity level, patient arrival pattern and age group. The expected result of the data analysis is to provide an effective translation of the real data to distributions that can be implemented in the simulation model.

The patient classification has a direct impact on the flow of a patient in the simulation model. Reviewing gathered data showed a complex relationship between the patient's need, the treatment processes to be applied and disposition of patients. To address such complex relationship, classifying patients into different categories was required. Data analysis helped to find the way to classify patients.

3.3.1. Patients classification based on activity time

Based on interviews with senior physicians, the long average LOS of BH crisis patients often cause congestions in the system. Therefore, patients were first classified into two groups of BH crisis patients and non-behavioral health crisis patients called regular patients. The two groups were separated by filtering the diagnosis and chief complaint records. After filtering patient records were selected and copied in different tabs in Excel for further analysis. Figure 3-7 shows how BH patients are separated.

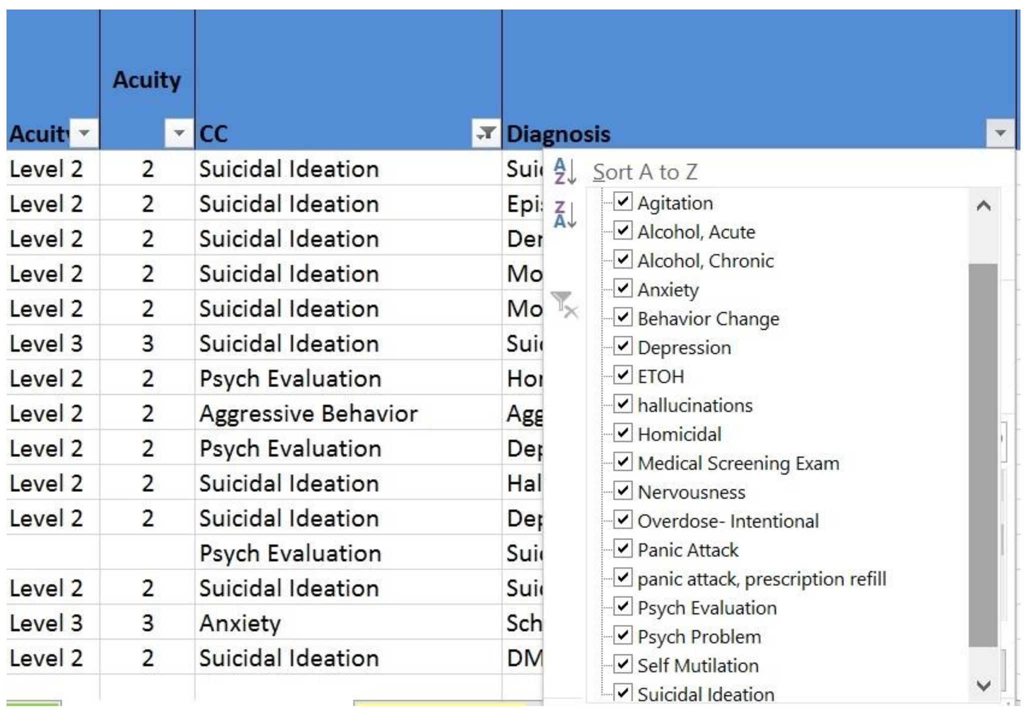


Figure 3-7 Export BH crisis patients from the data file

LOS starts from the time a patient enters the ED and get put into the system (registration) to the time he or she leaves the exam room of the ED (depart). For modeling purpose, the LOS was divided into registration time, triage time, roomed-to-deposition time, disposition-to-depart time, and the waiting time. Records of roomed-to-disposition and disposition-to-depart time for all patients in a two-month period in Oct and Nov 2016 were provided. Reviewing the data revealed a correlation between the disposition type (discharge, admit, and transfer) and the disposition-to-depart time. Therefore, the data headed to be further separated. As regular patients with disposition types of admitted and transferred were quite similar in terms of disposition-to-depart time, they are not differentiated considered in one group. After filtering data on the disposition type shown in Figure 3-8, patients are classified into five groups: admitted BH crisis patients, transferred BH crisis patients, discharged BH crisis patients, admitted/transferred regular patients and discharged regular patients. Records of patients with any other discharge type such as elopement and left without being seen were not used.

The roomed-to-disposition time is the time that a patient enters an exam room until the moment that decision is made to admit, transfer or discharge the patient. The disposition-to-depart time represents the time from disposition decision made for a patient until the moment that the patient leaves the exam room. Figure 3-8 depicts how the entire length of stay of a patient was separated into 6 main portions.

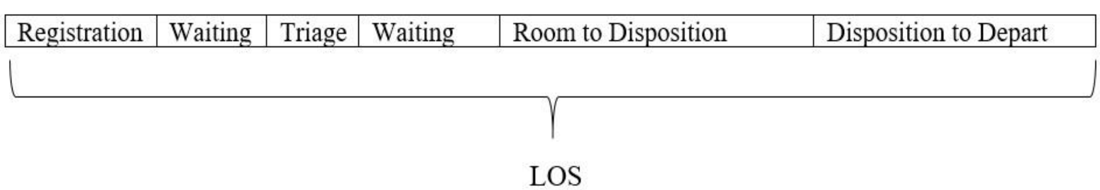


Figure 3-8 Length of Stay Separated into 6 main portions

For all five groups of patients, the registration time and triage time, as well as the separate records of roomed-to-disposition time and disposition-to-depart time are cleaned by deleting outlier data points. The outliers are found through sorting the data and discuss with the ED staffs. The outliers are usually a result of not changing the patient status in time in the computer system. For example, as it shown in Figure 3-9 they were two records of disposition-to-depart time that were found through discussion with the ED physicians. After confirming by the ED staff that such disposition-to-departure time would not happen in reality the records were deleted.

AA	AB	AC	AD	AE
Bed Requested to Admit	Dispo to AVS Prir	Dispo to Dischar	Dispo to Depart	Doc Assigned to Dispo
			1967	108
	0	1120	1120	240
			621	257
611			611	
			595	45
201			580	177
	574		579	182
541			541	210
520			520	26

Figure 3-9 Outliers in disposition-to-depart time data of transferred regular patients

After cleaning the data then Stat:: Fit the statistical software that comes with ProModel was used to find the best distribution fit for each set of data. These distributions were used as inputs to the simulation model.

Table 3-1 shows the number of data points used to fit the distributions and the best-fitted distribution of each group of patients. Figures A-1 to A-26 in the appendix 1 illustrate the autocorrelation test proves data points are independent followed by fitted distribution on each set of data. Figures also contain distribution rank and goodness of fit tests.

Table 3-1 Fitted distributions on roomed-to-disposition and disposition-to-depart time for all type of patients

<table>
<tr><th>Patient Type</th><th>Data</th><th colspan="2">Number of data points</th><th>Fitted distribution</th></tr>
<tr><td rowspan="2">Admitted BH Crisis Patients</td><td>Roomed-to-Disposition Time</td><td colspan="2">134</td><td>Loglogistic (17, 1.82, 95.7)</td></tr>
<tr><td>Disposition-to-Depart Time</td><td colspan="2">134</td><td>Loglogistic (2,2.6,145)</td></tr>
<tr><td rowspan="2">Transferred BH Crisis Patients</td><td>Roomed-to-Disposition Time</td><td colspan="2">174</td><td>Gamma (15.3, 1.08, 1.03e+003)</td></tr>
<tr><td>Disposition-to-Depart Time</td><td colspan="2">174</td><td>Loglogistic (3, 1.78, 130)</td></tr>
<tr><td rowspan="2">Discharged BH crisis Patients</td><td>Roomed-to-Disposition Time</td><td colspan="2">369</td><td>Pearson 6(16,266,1.84,1.82)</td></tr>
<tr><td>Disposition-to-Depart Time</td><td colspan="2">369</td><td>Pearson 6(2,22.5,1.92,1.41</td></tr>
<tr><td rowspan="3">Admitted/Transferred Regular Patients</td><td rowspan="2">Roomed-to-Disposition Time</td><td rowspan="2">1555</td><td>15</td><td>Weibull (427, 0.583, 0.00872)</td></tr>
<tr><td>1538</td><td>Beta (9.46, 546, 1.49, 4.86)</td></tr>
<tr><td>Disposition-to-Depart Time</td><td colspan="2">1555</td><td>Pearson 5(-79, 9.23, 1.83e+003)</td></tr>
<tr><td rowspan="4">Discharged Regular Patients</td><td rowspan="2">Roomed-to-Disposition Time</td><td rowspan="2">4072</td><td>337</td><td>Pearson 6(281,81.9,1.28,1.81)</td></tr>
<tr><td>3735</td><td>Beta(16,295,1.2,1.85)</td></tr>
<tr><td rowspan="2">Disposition-to-Depart Time</td><td rowspan="2">4072</td><td>38</td><td>Pearson 5(209, 2.91, 660)</td></tr>
<tr><td>4034</td><td>Inverse Weibull (7.74, 1.96, 0.0461)</td></tr>
</table>

Since the Stat:: fit was unable to find any good distributions to fit the 1555 data points of the admitted/transferred regular patients, roomed-to-disposition time. Through trial and error, the data set was divided into two sets, one with 15 and the other 1538 data points to find the best-fitted distribution for each. Later in the model, the two distributions were used along with an IF function to generate values with different percentages calculated from the ratio of data points. In this way, 15/1538 which is 0.97% of activity time were generated from Weibull distribution shown in Table 3-1, and the rest were generated from the other distribution, the Beta distribution shown in Table 3-1 for the roomed-to-disposition time of the admitted and transferred regular patients. Similarly, the same steps were taken to find two best-fitted distributions of roomed-to-disposition time and disposition-to-depart time to 4072 data points for the discharged regular patients.

3.3.2. Patient classification based on acuity level

The purpose of determining acuity level at triage in the ED was to prioritize incoming patients based on a one to five ESI level scales (level 1 being the most urgent and level 5 the least urgent). In the simulation model, ESI level was applied as an attribute to each patient at the arrival location to route the patient throughout the system. This attribute determines the routing of the patients from triage location as well as the priority of a patient getting into a room. Since patients enter to the ED from two different arrival locations, the data file was divided into two sets, walk-in patients and patients arrived by ambulances or police cars. In this work, they were called walk-in arrival and EMS/LAW arrival respectively. The data file included 1402 records of EMS/LAW arrivals and 5506 records of walk-in arrivals. The percentage of each level of ESI for walk-in arrivals and EMS/LAW arrivals were calculated. Two user distributions were defined in the model to assign ESI level to each patient at the arrival locations following percentage of each ESI level which is shown in Table 3-2.

Table 3-2 ESI level percentage at each arrival location

Arrival Location	ESI level 1	ESI level 2	ESI level 3	ESI level 4	ESI level 5
Walk-in Arrival	0.89%	24.94%	70.01%	3.86%	0.3%
EMS/LAW Arrival	0.02%	10.87%	63.07%	24.70%	1.34%

3.3.3. Patient classification based on the age group

Since the ED has two waiting areas, one for adults and the other for pediatrics, records were separated to determine the percentage of each and assign it as an attribute to the patients at the arrival locations. To accomplish this, patients were counted using COUNTIF function to find the number of patients at each age group described in data cleaning section. 6247 out of 6908 patients are an adult which accounts for 90.4%, and 661 are pediatrics which is 9.56%. A user distribution was defined based on these percentages to assign attributes to patients at the arrival locations.

3.3.4. Patient arrival pattern

At last, the arrival pattern of the patients was analyzed. For a patient arrived by ambulance with the low acuity value, a room is reserved before the patient arrives at the ED. Therefore, another attribute was used and assigned to each patient at the arrival locations to differentiate their arrival methods: by ambulances, police cars, and walk-ins.

197 patients out of 6908 (2.85%) arrived by police cars,1205 patients (17.45%) arrived by ambulances, and the rest (79.9%) are walk-in patients. An attribute was used to assign this arrival type value to each entity in the model.

Analyzing provided data and observations revealed that the number of patients arriving at the ED varies from hour to hour, with evening hours busier than early morning hours. In the data file records, the arrival date, hour and minute of each patient were separated using a function to foster the data analysis. Figure 3-10 shows how time and date are separated and copied in a new cell for walk-in patients using Excel functions. Same steps are taken to find a number of patients arrived at LAW/EMS arrivals.

	A	B	C	D
1	**Arrived**	**Date**	**Hour**	**Min**
2	10/10/16	10/10	04	35
3	10/10/16	10/10	04	57
4	10/10/16	10/10	08	25
5	10/10/16	10/10	09	15
6	10/10/16	10/10	10	48
7	10/10/16	10/10	11	31
8	10/10/16	10/10	11	55
9				
10	Cell	Formula		
11	B2	=RIGHT(LEFT(A2,6),5)		
12	C2	=LEFT(RIGHT(A2,4),2)		
13	D2	=RIGHT(A2,2)		

Figure 3-10 Separating arrival record to date, hour and minute

To find an average number of patients arriving at the ED on each day, patients were counted based on their arrival date. Figure 3-11 shows an example of COUNTIF function that was applied to find the number of patients arrived in a different date. For example, in cell C2 number of patient arrival dates equal to cell B2 which is October 10th were counted.

	A	B	C
1	Patients Arrival Date	Patients Arrive in	Number of visits on each day
2	10/10	10/10	65
3	10/10	10/11	81
4	10/10	10/12	74
5	10/10	10/13	71
6	10/10	10/14	59

Cell	Formula
C2	=COUNTIF($A2:$A4631,B2)

Figure 3-11 Counting number of patient arrived on each day

Statistical tests indicated that the numbers of patients arrived per day during the two-month period in the given data at the two arrival locations both follow a normal distribution as shown in Figure 3-12 and Figure 3-13.

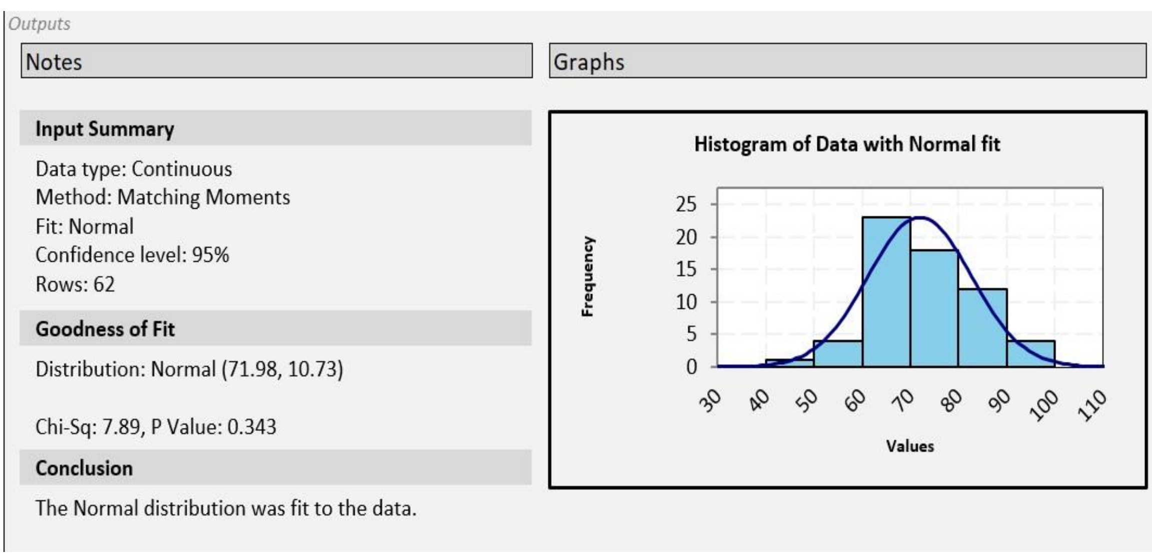


Figure 3-12 Fitted Distribution of Walk-in Arrival records

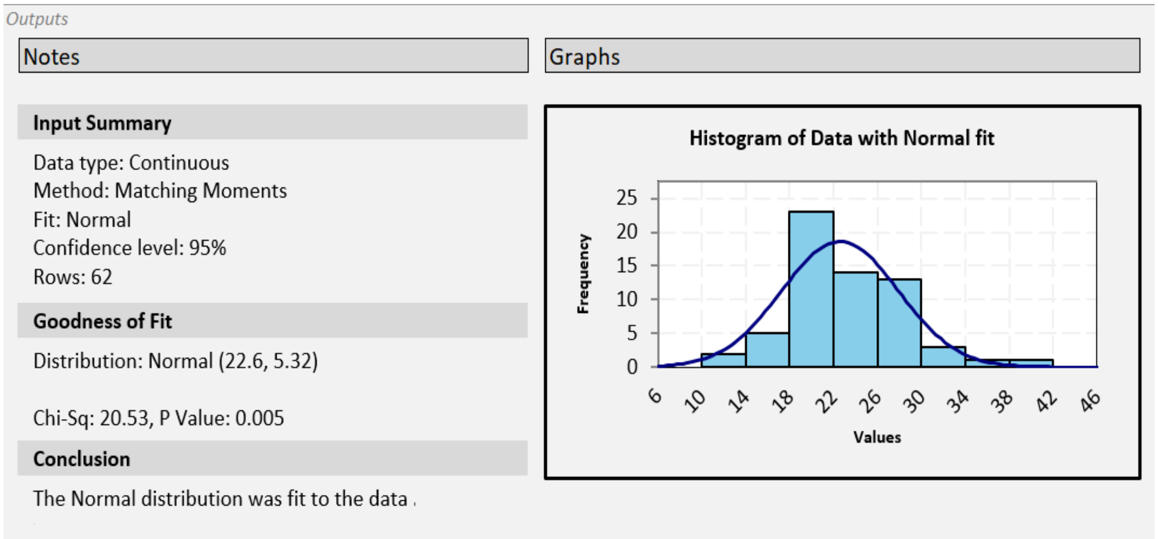
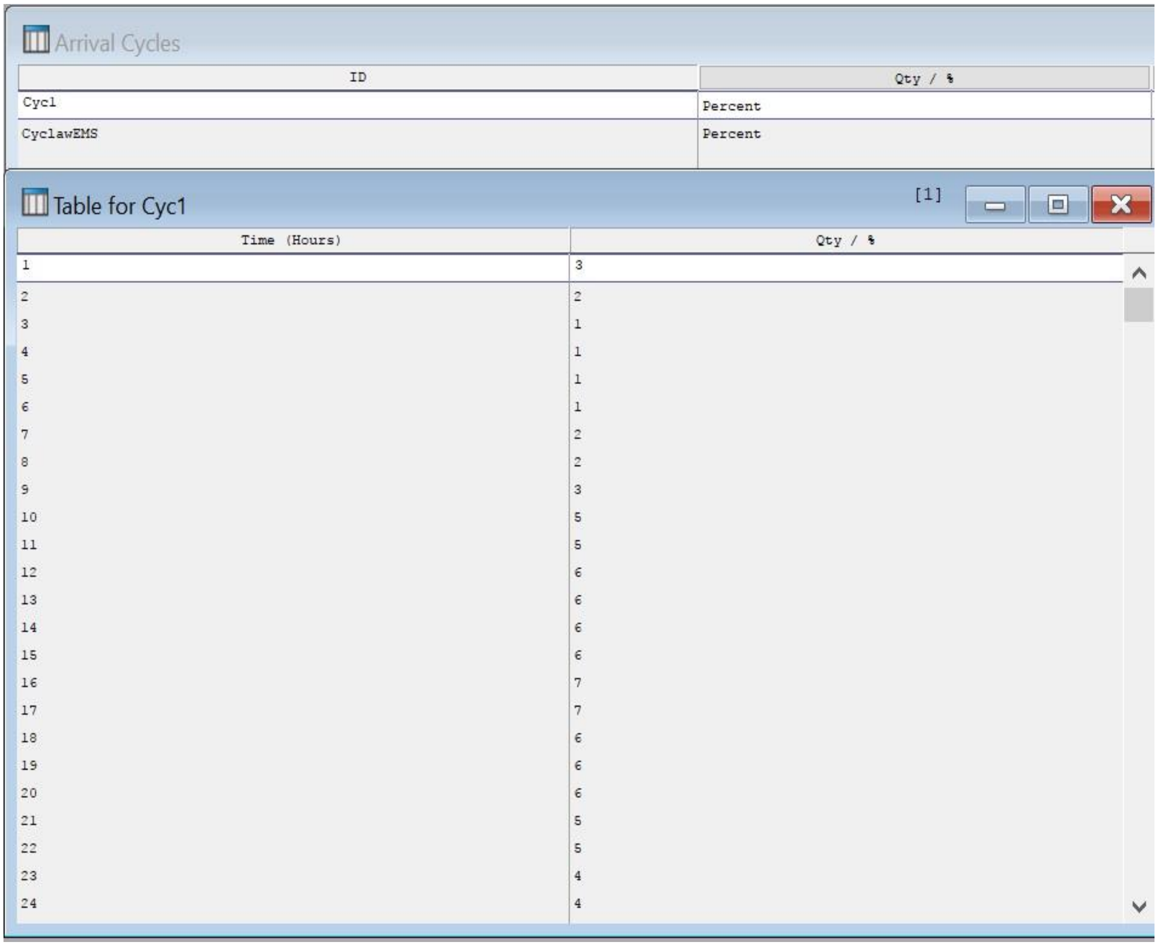


Figure 3-13 Fitted Distribution on EMS/LAW arrival records

The next step was to figure out how many patients usually arrive at each of the 24 hours during a given day. To do this, the number of patients arrived at each hour during the two-month period in the given data were counted using a COUNTIF formulation. Then the percentage of the number of patients arrived at each location were calculated. This was done for both arrival locations, the walk-in, and the EMS/LAW arrival. Figure 3-14 shows an example of the aforementioned percentages for arrival locations in the "Arrival cycle" in the ProModel.



Arrival Cycles

ID	Qty / %
Cyc1	Percent
CyclawEMS	Percent

Table for Cyc1 [1]

Time (Hours)	Qty / %
1	3
2	2
3	1
4	1
5	1
6	1
7	2
8	2
9	3
10	5
11	5
12	6
13	6
14	6
15	6
16	7
17	7
18	6
19	6
20	6
21	5
22	5
23	4
24	4

Figure 3-14 Walk-ins arrival cycle defined in ProModel

3.4. Entity flow diagram and process description

The end product of data collection and data analysis is the following entity flow diagram shown in Figure 3-15 accompanied with a detailed description of operations shown in Table 3-3.

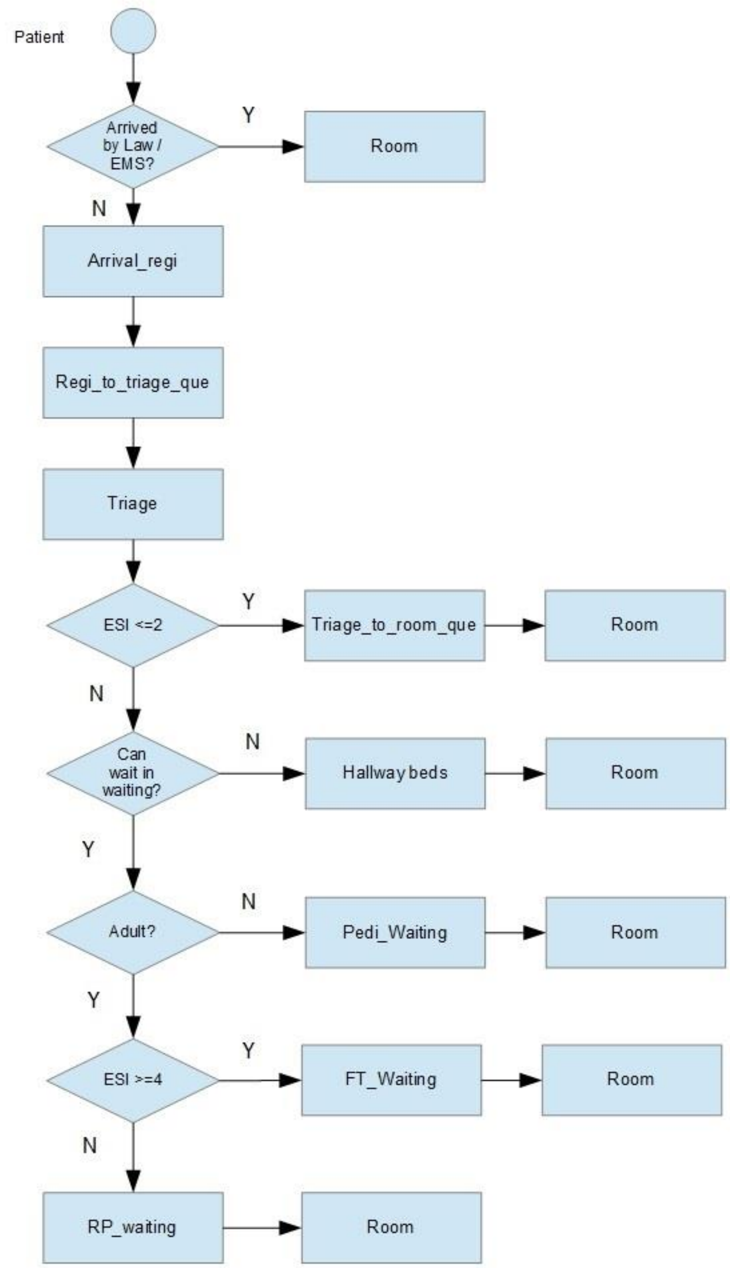


Figure 3-15 Entity Flow Diagram

Table 3-3 Operations description table

Location	Activity Time	Next Location	Move Trigger	Move Time	Move Resource
Arrival	None	Room	EMS or LAW arrivals		Aids/RN
		Arrival_reg	Walk-in arrivals		Aids/RN
Arrival_reg	U (3.5, 1.5)	Regi_to_triage_que	None	0.5min	None
Regi_to_triage_que	None	Triage	When triage is available		None
Triage	T (1, 4, 15)	Triage_to_room_que	a_ESI≤2 or if patient cannot wait in the waiting area	None	None
		Pedi_waiting	a_ESI≥3 and not an adult		Aids/RN
		FT_waiting	a_ESI≥4	0.5min	None
		RP_waiting	a_ESI =3	0.5min	None
Triage_to_room_que	None	Hallway Beds	No room available		Aids/RN
		Room	When room is available		Aids/RN
Pedi_waiting	None	Room	When room is available		Aids/RN
FT_waiting	None	Room	When room is available		Aids/RN
RP_waiting	None	Room	When room is available		Aids/RN
Hallway Beds	None	Room	When room is available		Aids/RN
Room	Roomed-to-disposition plus Disposition-to-depart time (Refer to Table 3-1)	Exit			

3.5. Simulation modeling

The following assumptions were made:

- Waiting area and all queues do not have limited capacity.
- Rooms at all zone except for trauma rooms are not prioritized.
- All patients arriving at walk-in arrival walk into the ED and do not need any nurse to be escorted with.
- RNs and Aids stay in main nurse station located in the center of ED when idle.
- All nurses are shared among all zones.
- Patient does initial registration at the registration desk and complete registration and payment happen right before discharge for all patients. This part is not modeled since it was included in deposition-to-depart time.
- For all patients waiting in the waiting room with the same condition first come first served rule was applied.
- Physicians activity, lab, and image were not modeled since the time is included in roomed-to-disposition time.

A discrete event simulation software, ProModel was used for this project. ProModel offers 2D animations and user interface to demonstrate improvement scenarios. ProModel uses more than 20 statistical distribution types to capture the system randomness. There are six key components used to model the system in ProModel and they are entities, attributes and user distributions, locations, resources and shifts, path networks and variables. Model logic describes after defining the key concepts.

3.5.1. Entity

Entities are dynamic objects that go through the system following defined processes. In the model, patients entering the ED are the only entity type and they are differentiated by attributes. The speed of the entities is set as 4 ft/s, the average human walking speed [75].

3.5.2. Attributes and user distributions

An attribute is attached characteristic to individual entities which by getting specific values can differentiate the entities. In the model, some of the attributes are used to control entities movement and route them through different paths between locations, while others are used for the model validation and debugging purposes. Table 3-4 and 3-5 shows the attributes defined in the model. Attributes such as a_Arrivaltype, a_Adult, a_Special_case, a_ESI, a_Stable and a_Need_hall_way would specify the priority to receive care, paths to travel between locations, and resource it would use. a_Starting_time, a_Roomed_time, a_Dispo_time, a_Depart_time, a_Triage_time, and a_LOS, track the time the entities spend in certain parts of the system. They are used to debug and validate the model as well.

Table 3-4 Attributes in the basic model 1

Attribute	Type	Arrival type	Value	User Distribution	Notes
a_Special_case	Integer	Walk-in	0	94%	Regular patient
			2	6%	BH crisis patient
		EMS	0	88%	Regular patient
			2	12%	BH crisis patient
		LAW	0	23%	Regular patient
			2	77%	BH crisis patient
a_ESI	Integer	Walk-in	1	0.02%	Based on patient's acuity level, 1 is the most urgent and 5 is the least urgent.
			2	10.87%	
			3	63.07%	
			4	24.70%	
			5	1.34%	

		EMS/LAW	1	0.89%	
			2	24.94%	
			3	70.01%	
			4	3.86%	
			5	0.3%	
a_Stable	Integer	EMS/LAW	0	20%	If BH Patient is not medically stable
			1	80%	IF BH Patient is medically stable

Table 3-5 Attributes in the basic model 2

Attribute	Type	Value	User Distribution	Notes
a_Arrivaltype	Integer	1	3%	LAW Arrival
		2	21%	EMS Arrival
		3	76%	Walk-ins
a_Adult		0	10%	Pediatric patient
		1	90%	Adult patient
a_Need_hall_way		0	80%	If patient can wait in the waiting room
		1	20%	If patient needs to wait in a hallway bed
a_Starting_time	Real			Arrival time
a_Roomed_time				Roomed time
a_Dispo_time				Disposition time
a_Depart_time				Departure time
a_LOS				Length of stay from arrival to departure
a_Triage_time				Triage time

The attribute “a_Need_hall_way” was used in the model to differentiate patients who can wait in the waiting room from those who cannot due to their health condition. Assuming 80 percent of patients can wait in the waiting room and the rest 20 percent have to go to hallway beds to wait, this attribute was assigned to the entities using a user distribution. Likewise, the attribute “a_Stable” represents the medical stability of BH crisis patients.

3.5.3. Locations

Locations represent places that each entity and resources interact with each other. Processes on the entities happen in locations. Location in this model was built based on the ED layout. Locations can be defined as a queue in the model, where entities line up to get processed. Waiting for lines such as waiting area to triage room and triage room to a care room defined as queues in the model. Table 3-6 shows locations in the ED model and the corresponding location in the ED.

Table 3-6 Locations in the basic model

Locations built in the model	Location in the ED	Capacity	Note
EMSLAW_Arrival	Ambulance entrance	Infinity	
Walkins_Arrival	Main entrance	Infinity	
Arrival_reg	Registration desk	1	
Triage	Triage room	1-2	A variable control the capacity of triage room
Waiting	Waiting room	Infinity	
Pedi_waiting	Pediatric waiting room	Infinity	
Hall1-Hall6	Hallway beds These beds are in the hallway	1	
Nurse_station	Nurse and physician station	20	
R2 through R7	Rooms 2 to 7. These rooms are in the red zone.	1	
B1, B8,B9,B10,B11,B12	Rooms 1,8,9,10,11,12 These rooms are in the blue zone	1	
P14-P17	Rooms 14 to 17 These rooms are in the purple zone	1	
FT1-FT4	Rooms FT1 to FT4 These rooms are in the fast track zone	1	

Y18, Y19, Y21-Y24	Rooms 18,19,21,22,23,24 These rooms are in the yellow zone	1	
Triage_to_room_que	Patients wait in this line to get into a room after being triaged	Infinity	In reality, this queue is in the waiting room area.
Regi_to_triage_que	Patients wait in this line to get triaged after registration	Infinity	In reality, this queue is in the waiting room area.
FT_waiting	Patients wait in this area to get into fast-track zone	Infinity	In reality, this is waiting room area.
RP_waiting	Patients wait in this area to get into blue, red, yellow or purple zones	Infinity	In reality, this is waiting room area.

Due to modeling purposes, the capacity of waiting locations was set to infinity. Triage room capacity was controlled by a variable, the v_triage_capacity. This variable starts with an initial value of 1 and can increase to 2 when the number of people in the regi_to_triage_que exceeds 5, to represent that when there are more people waiting in the waiting room area to be triaged, another nurse would help the triage process in real practice.

3.5.4. Resources and shifts

A resource represents units such as staff, equipment, or space that an entity may use to get processed or move through the system. Resources can be scheduled by the user to define how and when they can be used. In the basic model, the resources are registered nurse (RN) and nursing assistant (Aids). All resources have the "entity search rule" set as going to the longest waiting entity and they return modeled to their station when idle. Table 3-7 shows the resources defined in the basic model.

Table 3-7 Resources in the basic model

Resources built in the model	Resources in the ED	Number of staff
RN	Register nurse	25
Aids	Nurse aids	10

The information regarding the personnel resources available to the Hospital ED was provided. The ED is staffed with one charge nurse and more than equal to 4 nurses. The nurses work on an 8-or-12-hour shift. In each 24-hour day, two nurses will each take a 12-hour shift, and the rest take 8-hour shifts. 10 nurse aids work on 8 or 12 hours shifts too. This scheduling scheme serves two purposes: It provides additional nurse support during times of the day in which the number of patients seeking care at the ED is higher, and it enables a smoother transition of patient care for those patients who begin care while the first shift nurse is on duty and end their care with the nurse on the second shift. The nurses described here are dedicated to ED patient care and do not provide care to other patients in the Hospital. In the basic model, it was assumed that nurses are following a fixed scheduling scheme all days of a week.

3.5.5. Path network

The path network included several paths connected to define the route for entities and resources to travel between locations. In the model one path network including 91 nodes and 92 paths is defined. Each location has a node connected to it and each pair of nodes are connected by a path. The exception is that there is one path blocked in the ED which is from purple zone to the yellow zone rooms because the purple zone is locked. All resources and entity are moving on the one defined path network. To represent the actual system, path network lengths are set with estimation of distances between nodes.

3.5.6. Variables

Variables were used to control and monitor the model as well as defining logics within the model. Table 3-8 shows the variables and their type defined in the basic model.

Table 3-8 Table of variables in the basic model

Variable	Notes
v_Num_in_triage_to_room_q	Number of patients waiting to get into a room after being triaged
v_Num_in_waiting_room	Number of patients waiting in the waiting room area
v_Num_in_pediwaiting_area	Number of patients waiting in the pediatric waiting room area
v_Total_num_in_waiting	Total number of patients waiting in the waiting areas
v_Num_in_reg_to_tri_que	Number of patients waiting to get triaged after registration
v_Triage_capacity	Capacity of the triage room
v_Num_in_arrival	Number of patients at walk-in arrival
v_Num_in_Ft_waiting	Number of patients waiting to get into fast-track rooms
v_Num_in_RP_waiting	Number of patients waiting to get into blue, red, purple, yellow zone rooms

All the variables were set to be integers in terms of their type. All variables except "v_Triage_capacity" were used to calculate a total number of patients waiting. A total number of patients waiting later was used for verification and validation purpose. "v_Triage_capacity" is used to control the capacity of the triage room. Whenever the number of patients needs to be triaged exceeded five the triage capacity set to increase to two. So, another triage nurse was modeled to go to a triage room and help.

3.6. Modeling logic

Patients arrive at two arrival locations. Walk-in patients go to the registration desk, wait for a few minutes generated from the uniform distribution with a maximum of 3.5 minutes and a minimum of 1.5 minutes. Then the patient goes to the registration to triage queue to get into the triage room afterward. EMS/LAW arrival patients were routed directly to the rooms, with higher priority to the red and blue zone rooms. Medically stable BH crisis patients arriving by EMS/LAW were routed to purple zone rooms and fast-track rooms if the purple zone rooms are full. Then they get triaged in the room. For patients in the triage room, they waited for a few minutes generated from the triangular distribution with an upper limit of 15 minutes, the lower limit of 1 minute, and mode of 4 minutes, that represent the triage time. After being triaged, patients with ESI level 1 and 2, and those who cannot wait in the waiting room due to their health condition (identified by an attribute) regardless of their ESI level were being routed to the rooms. If all the rooms were occupied, they were routed to the hallway beds. Patients with ESI level of 3,4 and 5, based on their age group (identified by an attribute), were routed to the waiting area or pediatric waiting room. Following code represents the way that patients are routed after being triaged.

```
1: Wait T(1, 4, 15) /*Triage time */
2: Triage_time=Clock()
3: If Special_case=2 /*BH Crisis patients*/ Then
4: {Graphic 2
5: if Rand(100)> 20 Then Route 4 /*80% of BH patients go to Purple zone and FT*/ Else Route 7 /* 20% of BH
patients go to Blue, red and yellow zones */}
6: If Special_case=0 /*Regular patients */ Then
```

```
{Graphic 5
If ESI <= 2 Then Route 8 /*Red, blue, yellow zones and hallway beds (lowest priority) and triage to room to
queue if all rooms are occupied*/
Else {If A_Need_hall_way = 1 Then Route 8 Else
     {If Adult=1 then Route 1 /*waiting room */ Else {Graphic 6 Route 2 /*Peditric waiting area */}}
     }
}
```

Patients with lower ESI level (1 and 2) have a priority to go to rooms number 1 to 12, located in red and blue zones since these rooms were relatively better equipped. If those rooms become full, patients with the same condition will be routed to yellow zone rooms. Patients with the BH crisis will be routed to the purple zone rooms if they have medical stability, otherwise will be routed to red, blue or yellow zone rooms to get treatment and stay there. There might be situations in which these patients need to be transferred to the purple zone after becoming medically stable. But for simplifying reason, it is not modeled as the number of BH crisis patients with this condition are negligible.

Patients with ESI level 4 and 5 in the waiting area are routed to the fast-track rooms while ESI level 3 patients are routed to red, blue, yellow zone rooms. For patients in the hallway bed, with an ESZ level higher than Z, those have the highest priority to get into a room higher than those waiting in the triage to room queue or waiting area.

Room 2 and 3 in the red zone and room 1 and 12 in the blue zones have the lowest priority for ESI level 3 patients since the policy is to keep those rooms open for the patients with lower ESI levels (1 and 2). Patients are all taken to the rooms by RNs or Aids in the ED. The same logic is used for patient waiting in the pediatric waiting room.

In all rooms, the patient treatment time and the disposition-to-depart were generated by defined distributions for each type of patient described in section 3.3.1 and listed in Table 3-1. Since the activities in all rooms are the same, a macro was written and placed as the activity in all treatment rooms. The code in the macro is:

```
1: If Special_case=0 Then
2: {Real X
3: X= Rand(10000)
4: If x > 2760 /*Discharged Regular Patients*/ then
5: {{If Rand(100) > 8 then Wait B(1.2, 1.85, 16, 295) Else Wait 281+P6(1.28, 1.81, 81.9)}/*Roomed to disposition time*/
6: {If Rand(10000) > 93 then Wait -7.74+(1./0.0461)*(-LN(U(0.5,0.5)))**(-1./1.96) Else Wait 209+P5(2.91, 660)}/*Disposition to Depart*/
7: Else /*Admitted/Transferred Regular Patients*/
8: {{If Rand(10000) > 97 Then Wait B(1.49, 4.86, 9.46, 546) Else wait B(0.372, 1.,427, 2.76e+003)}/*Roomed to Disposition time*/
9: wait 129+259*(1./((1./U(0.5,0.5))-1.))**(1./6.52) /*Disposition to Depart*/}}
10:If Special_case=2 /*BH crisis Patients*/ Then
11: {Real Y
12: Y=Rand(100)
13: If Y <= 20 /* Admitted BH Crisis Patients*/ Then
14: {wait 17+95.6*(1./((1./U(0.5,0.5))-1.))**(1./1.82) /*Roomed to Disposition time*/
15: Wait 2.+145*(1./((1./U(0.5,0.5))-1.))**(1./2.61)  /*Disposition to Depart*/}
16: If Y > 20 And Y <= 55 /*Transferred BH crisis Patients */ Then
17: {Wait 16+W(1.07, 1.15e+003) /*Roomed to Disposition time*/
18: Wait P6(1.28, 4.85, 589) /*Disposition to Depart*/ }
19: If Y > 55 Then /*Discharged BH crisis Patients */
20: {Wait 16+P6(1.84, 1.82, 266) /*roomed to disposition time*/
21: {If rand(10000) < 136 Then Wait T(1165,1675,1847) Else wait W(0.7,55.71)} /*Disposition to Depart*/}}
```

The patient leaves the ED after completion of the roomed-to-disposition and disposition-to-depart time based on if they are discharged, admitted or transferred. The occupied room is closed for cleaning purposes right after that. This was modeled as a downtime of 5,7 and 15 minutes at the location following the minimum, mode, and maximum values.

3.7. Verification and validation

Since the simulation modeling was done in different stages, each stage of it was debugged separately during model development to make sure they were functioning properly. Processes such as arrival process, patient triage process and treatment process including distributions representing patient treatment time were monitored with a focus on ensuring that the model works as expected. A one-week warm-up time was set up for the model to reach a stable state. To ensure that one-week was enough as a warm-up time, the total number of patients waiting was tracked by a variable to compare with the actual number. After running the model and analyze the results, some problems emerged, and they were:

- Triage-to-room-queue built up ─ One important observation was the number of patients waiting in waiting area and queues to get into the exam rooms. The problem was in the triage-to-room-queue where the number of patients waiting in the queue increased constantly as the model ran and never got reduced. This signaled an error in the model that entities were blocked at a certain location. This was not the bottleneck in the real system so it could be the result of a big gap between the treatment time and the rate of arrivals. Therefore, the arrival pattern and treatment times were reviewed but no issues were found there. In the next attempt, entities were tracked step by step using the trace feature as the model was running. Finally, it was discovered that the speed of nurses in the model was set incorrectly causing the queue to build up as no nurse was available to escort the patients to the exam rooms as they were moving extremely slow. To fix the problem, the distances and nurses' speed were both modified.

- Fast-track patients stuck in the waiting room ─ Another issue identified in verification was that patients of acuity level 4 and 5 stuck in the waiting room and would not get into empty rooms in the fast-track zone because a patient of ESI level 3 was in front of them waiting for an empty room in other zones. To fix this issue, dummy locations were built in the waiting room to separate the waiting for patients who can go to fast-track rooms from the rest. In this way, patients of ESI level 4 and 5 and patients of ESI level 3 wait in two separate waiting locations and one goes to fast-track rooms while the other goes to the red, blue and yellow zones.

After solving the previous problems, the model was validated by comparing the statistics derived from the given data and the model results was obtained from running the model for 25 replications, with each run being 9 weeks long and a one-week warm-up. Two issues were identified in this step:

- Rooms utilization ─ Results showed that room utilization for some rooms is relatively higher than others. In reality, the ED charge nurse always balances the utilization of rooms in different zones by sending patients to different rooms when needed. To solve this problem, the order of rooms in the patients routing out of waiting room and triage room were changed to balance the room utilization. After the change, all the rooms except for rooms 1, 2, 11, and 12 had similar levels of utilization. The four rooms, 1, 2, 11 and 12 in blue and red zone still have lower utilization rate as expected because they are kept for patients with lower ESI levels and or reserved as the trauma room.

- Long LOS time ─ Comparing statistics from data file and simulation results revealed about 30 minutes' differences in the average LOS of discharged regular patients. Attributes were used to track admission time, triage time, disposition time and depart time for each type of patients. Reviewing values of these attributes for each group of patients showed that the distribution function used for the roomed-to-disposition time for discharged regular patients generated values greater than expected. The problem was solved once the distributions were fitted on the data again using Stat:: Fit and exported directly to ProModel.

After the errors were fixed, three performance measures were chosen to compare real data and model results. The data andmodel results of LOS and triage-to-roomed time which represents the patients wait in the waiting room were compared. Attributes were used to calculate these two times for each patient in the model. Averages were calculated and compared. Table 3-9 and 3-10 show the comparison compares the parameters values.

Table 3-9 Triage-to-roomed (actual data versus baseline model results)

	Triage to roomed time (minutes)
Triage to roomed Actual Data	46
Model Result	42

Table 3-10 Length of stay for each type of patients (actual data versus baseline model results)

	Average length of stay	
	Actual	**Baseline**

Discharged regular patients	227	217
Admitted/transferred regular patients	312	331
Admitted BH crisis patients	447	439
Transferred BH crisis patients	1332	1353
Discharged BH crisis patients	720	705

3.8. Experiments

Once the basic model was verified and validated, experiments were run to test the impact of certain improvements in terms of reducing the average LOS and waiting time. Since the basic model was built to test the impact of the bottlenecks in disposition-to-depart time for admitted and transferred patients, as well as the roomed time of BH crisis patients, four different scenarios were first built as experiments. Hypothesis tests with a confidence level of 95 percent are conducted for each experiment. The first four experiments include:

i) Shortening the disposition-to-depart time for regular admitted or transferred patients by half.

Based on observations in the ED, discussions with the ED physicians and staffs, examining the data, the time it takes for an admitted patient to leave the ED and go to the hospital is a long bottleneck. Some possible reasons for this delay are:

- There is no available bed in the hospital
- The ED physicians cannot reach hospitalists to facilitate an admission since they are too busy.
- Nurses are busy with patients and they will not come downstairs to transfer patients to the hospital. Many times, such delay happens between hospital nurse shifts.

In this scenario, the disposition-to-depart time for the admitted and transferred regular patients in the given data were cut by half and a new distribution was fitted. Since it is not likely to get a patient from ED to the hospital in less than 5 minutes, any data points less than 10 minutes were not changed. Using the new distribution fitted from the modified data, as the new disposition-to-depart time, the scenario is again run for 25 replications with the same length (9 weeks with 1-week warm-up). Table 3-11 shows the improvement in the average LOS for five different groups of patients in comparison with the baseline model. Table 3-12 shows the improvement in patient waiting time, which is the triage-to-roomed time. it is very important to improve this time because patients may leave without being seen due to long waiting.

Table 3-11 Triage-to-roomed time comparison (First experiment versus baseline data)

	Waiting time / Triage to roomed time (minutes)		
All Patients	**Baseline**	**Scenario 1**	**Reduction Percentage**
	42	28	33%

Table 3-12 Length of stay comparison (First experiment versus baseline data)

	LOS (minutes)		
	Baseline	**Scenario 2**	**Reduction Percentage**
Discharged regular patients	217	206	5%
Admitted/transferred regular patients	331	249	25%
Admitted BH crisis patients	399	290	27%
Transferred BH crisis patients	1353	1258	7%
Discharged BH crisis patients	705	678	4%

Hypothesis tests with a confidence level of 95 percent were conducted with 25 replications. The first test is as follows:

H0: Shortening the disposition-to-depart time for admitted and transferred patients in half will not improve the average LOS.

H1: Shortening the disposition-to-depart time for admitted and transferred patients in half will improve the average LOS

Result illustrated in table 3-13 shows at 95% confidence level, the null hypothesis is rejected for all groups of patients except for the discharged BH crisis patients. This means that the first scenario can improve the LOS for all group of patients except discharged BH crisis patients. This means that the first scenario can improve the LOS for all group of patients except discharged BH crisis patients.

Table 3-13 Hypothesis test on the result of the first experiment

Scenario 1	Regular Patients (Discharged)	Regular Patients (Admitted/ Transferred)	BH crisis Patients (Discharged)	BH crisis Patients (Admitted)	BH crisis Patients (Transferred)
Average	-23.26	-93.45	-11.24	-153.89	-94.55
STD DEV	18.37	17.95	190.52	81.51	139.45
Confidence	0.05	0.05	0.05	0.05	0.05
HW	7.58	7.41	78.64	33.64	57.56
UL	-15.67	-86.04	67.40	-120.25	-36.98
LL	-30.84	-100.86	-89.88	-187.54	-152.11
Rejected	X	X		x	x

With the proposed change,

- For regular patients that are discharged, the LOS will be shortened by 15.67 to 30.84 minutes with an average of 23.26 minutes,

- For admitted or transferred regular patients, the LOS can be shortened by 86.04 to 100.86 minutes with an average of 93.45 minutes,
- For discharged BH crisis patients the LOS can be increased by up to 67.40 minutes or reduced by up to 89.88 minutes with an average reduction of 11.24 minutes,
- For admitted BH crisis patients the LOS can be reduced by 120.25 to 187.54 minutes with an average of 153.89 minutes,
- For transferred BH crisis patients the reduction is in the range of 36.98 to 152.11 minutes with the average of 94.55 minutes.

ii) Shortening one-third of disposition-to-depart time for admitted or transferred regular patients.

If the hospital is not able to shorten the current disposition-to-depart time for admitted or transferred regular patients by half, what will be the impact if it would be shortened by one third? To answer this question, the second scenario was modeled by shortening the disposition-to-depart time of the given data by one third and fitting a new distribution. Results in Table 3-14 show a 19 percent reduction of triage-to-roomed time and Table 3-15 shows a significant impact of this scenario in terms of reducing the LOS for the admitted/transferred regular patients and admitted BH crisis patients.

Table 3-14 Triage-to-roomed time comparison (the second experiment versus baseline data)

	Waiting time / Triage to roomed time (minutes)		
All Patients	**Baseline**	**Scenario 2**	**Reduction Percentage**
	42	34	19%

Table 3-15 Length of stay comparison (The second experiment versus baseline data)

	LOS (minutes)		
	Baseline	**Scenario 2**	**Reduction Percentage**
Discharged regular patients	217	212	2%
Admitted/transferred regular patients	331	277	16%
Admitted BH crisis patients	399	327	18%
Transferred BH crisis patients	1353	1283	5%
Discharged BH crisis patients	705	706	0%

Hypothesis tests with a confidence level of 95 percent were conducted with 25 replications of same length and warm-up to verify the impact on the average LOS for each group of patients. The test is as follows:

H0: Shortening one-third of the disposition-to-depart time for admitted and transferred patients will not improve the average LOS

H1: Shortening on a third of the disposition-to-depart time for admitted and transferred patients will improve the average LOS

The result shown in Table 3-16 depicts that at 95% confidence level, the null hypothesis is rejected for all regular patients and admitted BH crisis patients. This means that the second scenario can improve the LOS for all groups of patients except discharged and transferred BH crisis patients.

Table 3-16 Hypothesis test on the result of the second experiment

Scenario #2	Regular Patients (Discharged)	Regular Patients (Admitted/ Transferred)	BH crisis Patients (Discharged)	BH crisis Patients (Admitted)	BH crisis Patients (Transferred)
Average	-10.64	-56.14	8.57	-75.12	-55.14
STD DEV	24.83	22.10	134.74	106.19	165.76
Confidence	0.05	0.05	0.05	0.05	0.05
HW	10.25	9.12	55.62	43.83	68.42
UL	-0.40	-47.01	64.19	-31.28	13.28
LL	-20.89	-65.26	-47.05	-118.95	-123.57
Rejected	X	X		X	

With the proposed change,

- For discharged regular patients, the LOS will be shortened by 0.40 to 20.89 minutes with an average of 10.64 minutes,
- For admitted or transferred regular patients the LOS can be shortened by 47.01 to 65.26 minutes with an average of 56.14 minutes,
- For discharged BH crisis patient this change can increase the LOS by 64.19 and reduce it by 47.05 minutes,
- For transferred BH crisis patients the LOS can increase by 13.28 minutes and reduce by 123.57 minutes with the average of 55.14 minutes,
- For admitted BH patients the reduction in LOS is in the range of 31.28 to 118.95 minutes with the average of 75.12 minutes.

However, for two groups of transferred and discharged BH crisis patients, the LOS can be increased in this scenario. Therefore, with the confidence level of 95%, the first scenario may not improve the LOS for these two groups of patients.

iii) Shortening the roomed-to-disposition time for BH crisis patients to half.

Over the past 40 years, the request for service for BH crisis patients has been shifted away from inpatient facilities [76]. Increasing number of psychiatric patients in the ED caused overcrowding of the department. Besides that, ED physicians face two challenges evaluating these types of patients. The first challenge is to how appropriately manage and accurately assess these patients. The second relates to the difficulties physicians face treating unwillingly admitted patients [76]. By reviewing data and having a fluent discussion with the hospital administrator, it was understood that the treatment of BH crisis patients takes longer than regular patients due to the medical clearance tests and required before the initial physician assessment. Besides, most of these patients need psychiatrist visit before departing. For example, a patient with alcohol intoxication, besides the regular blood alcohol level test, needs to be monitored by a nurse for a period to determine if the symptoms resolved or not to continue the further treatment. There are some best practices suggested reducing the treatment time for BH crisis patients like using telemedicine when a psychiatrist is not available or busy to reduce the LOS [76]. The proposed scenario is simulated to show the hospital administrators how reducing the treatment time for BH crisis patients would affect the average LOS of those patient group as well as others. The roomed-to-disposition time for discharged BH crisis patients was reduced to half. A new distribution was fitted to the given data to represent the roomed-to-disposition time. Table

3-17 shows the 24% reduction in triage-to-roomed time and Table 3-18 illustrates the 40% improvement in the average LOS of discharged BH crisis patients.

Table 3-17 Triage-to-roomed time comparison (The third experiment versus baseline data)

	Waiting time / Triage to roomed time (minutes)		
	Baseline	**Scenario 3**	**Reduction Percentage**
All Patients	42	32	24%

Table 3-18 Length of stay comparison (The third experiment versus baseline data)

	LOS (minutes)		
	Baseline	**Scenario 3**	**Reduction Percentage**
Discharged regular patients	217	210	3%
Admitted/transferred regular patients	331	324	2%
Admitted BH crisis patients	399	397	0%
Transferred BH crisis patients	1353	1354	0%
Discharged BH crisis patients	705	424	40%

Hypothesis tests with a confidence level of 95 percent were conducted with 25 replications of same length and warm-up to verify the impact on the average LOS for each group of patients. The test is as follows:

H0: Shortening the roomed-to-disposition time for discharged BH crisis patients in half will not improve the average LOS

H1: Shortening the roomed-to-disposition time for the discharged BH crisis patient in half will improve the average LOS

Results in Table 3-19 show that at 95% confidence level, the null hypothesis is rejected for all groups of patients except for the transferred BH crisis patients.

Table 3-19 Hypothesis test on the result of the third experiment

Scenario 3	Regular Patients (Discharged)	Regular Patients (Admitted/ Transferred)	BH crisis Patients (Discharged)	BH crisis Patients (Admitted)	BH crisis Patients (Transferred)
Average	-15.58	-14.02	-65.80	-58.32	24.27
STD DEV	18.53	16.41	81.05	90.92	149.71
Confidence	0.05	0.05	0.05	0.05	0.05
HW	7.65	6.77	33.46	37.53	61.80
UL	-7.94	-7.24	-32.34	-20.79	86.06
LL	-23.23	-20.79	-99.25	-95.85	-37.53
Rejected	X	x	x	X	

With the proposed change,

- For discharged regular patients the LOS will be shortened by 7.94 to 23.23 minutes with an average of 15.58 minutes,
- For admitted and transferred regular patients the reduction is in 7.24 to 20.79 minutes range with the average of 14.02 minutes,
- For discharged BH crisis the LOS can be shortened by 32.34 to 99.25 minutes with the average of 65.80 minutes,
- For admitted BH crisis the LOS can be shortened by 20.79 to 95.85 minutes with the average of 58.32 minutes,
- For the transferred BH crisis patients the LOS can be increased by up to 86.06 minutes and reduced by up to 37.53 minutes.

iv) Shortening one-third of the roomed-to-disposition time for BH crisis patients.

If the hospital is not able to shorten the current roomed-to-disposition time by half, what will be the impact if it would be shortened by one third? To answer this question, the fourth scenario was modeled by shortening the roomed-to-disposition time of the given data by one third and fitting a new distribution. The results in Table 3-20 show 17% reduction in waiting time and Table 3-21 depicts the impact of this scenario on LOS.

Table 3-20 Triage-to-roomed time comparison (The fourth experiment versus baseline data)

	Waiting time / Triage to roomed time (minutes)		
All Patients	**Baseline**	**Scenario 4**	**Reduction Percentage**
	42	35	17%

Table 3-21 Length of stay comparison (The fourth experiment versus baseline data)

	LOS (minutes)		
	Baseline	**Scenario 4**	**Reduction Percentage**
Discharged regular patients	217	213	2%
Admitted/transferred regular patients	331	327	1%
Admitted BH crisis patients	399	397	0%
Transferred BH crisis patients	1353	1375	0%
Discharged BH crisis patients	705	519	26%

Hypothesis tests with a confidence level of 95 percent were conducted for all 25 replications. The fourth test is as follows:

H0: Shortening one-third of the roomed-to-disposition time for discharged BH crisis patients will not improve the average LOS.

H1: Shortening one-third the roomed-to-disposition time for the discharged BH crisis patients will improve the average LOS.

Table 3-22 shows the result of a hypothesis test. The outcome proves that the null hypothesis is rejected for all groups of the patient except transferred BH crisis patients. For transferred BH crisis patients, the LOS will be reduced by 29.34 and can increase by 101.21. Therefore, the fourth scenario will not improve the LOS for this group. But for the rest of groups with a confidence level of 95 percent, this scenario will improve the LOS.

Table 3-22 Hypothesis test on the result of the fourth experiment

Scenario 4	**Regular Patients (Discharged)**	**Regular Patients (Admitted/ Transferred)**	**BH crisis Patients (Discharged)**	**BH crisis Patients (Admitted)**	**BH crisis Patients (Transferred)**
Average	-14.56	-17.13	-239.26	-58.32	35.94
STD DEV	17.92	16.21	154.56	90.92	158.14
Confidence	0.05	0.05	0.05	0.05	0.05
HW	7.40	6.69	63.80	37.53	65.28
UL	-7.17	-10.44	-175.46	-20.79	101.21
LL	-21.96	-23.82	-303.06	-95.85	-29.34
Rejected	X	X	x	X	

With the proposed change,

- For regular patients that are discharged, the LOS will be shortened by 7.17 to 21.96 minutes with an average of 14.56 minutes,
- For admitted or transferred regular patients, the LOS can be shortened by 10.44 to 21.96 minutes with an average of 17.13 minutes,

- For discharged BH crisis patients the reduction is in the range of 175.46 to 303.06 minutes with the average of 239.26 minutes.
- For admitted BH crisis patients the LOS can be reduced by 20.79 to 95.85 minutes with an average of 58.32 minutes,
- For transferred BH crisis patients the LOS can be increased by up to 101.21 minutes or reduced by up to 29.34 minutes with an average reduction of 11.24 minutes.

v) Adding a discharge lounge.

After reviewing the current design of the ED and having discussions with the physicians in charge of ED about the best practices reviewed in the literature, one of the applicable best practices in the ED was chosen to be modeled. Adding a discharge lounge to improve the flow of the patients by moving the patient from rooms to the discharge lounge after being dispositioned. Discharge lounge was added to the model with the capacity of 7 patients. Table 3-23 and 3-24 shows the results of the LOS and waiting time by adding discharge lounge to the model. Results show that adding discharge lounge will not improve the LOS except for admitted or transferred regular patients. However, as it is shown in Table 3-23 adding discharge lounge can reduce the waiting time by 79%.

Table 3-23 Triage-to-roomed time comparison (the fifth experiment versus baseline data)

	Waiting time / Triage to roomed time (minutes)		
All Patients	**Baseline**	**Scenario 5**	**Reduction Percentage**
	42	9	79%

Table 3-24 Length of stay comparison (The fifth experiment versus baseline data)

	LOS (minutes)		
	Baseline	Scenario 5	Reduction Percentage
Discharged regular patients	217	218	0%
Admitted/transferred regular patients	331	302	9%
Admitted BH crisis patients	399	394	1%
Transferred BH crisis patients	1353	1356	0%
Discharged BH crisis patients	705	701	1%

A hypothesis test was conducted to verify the impact of this experiment on the average LOS for all group of patients. The test is as follows:

H0: Adding discharge lounge will not improve the average LOS

H1: Adding discharge lounge will improve the average LOS

Results presented in Table 3-25 shows that at 95% confidence level, the null hypothesis is rejected for all groups of patients except for transferred BH crisis patients. This means this scenario can improve the LOS of all groups except for the transferred BH crisis patients.

For instance, the LOS will be reduced by 41.49 to 57.29 minutes with the average of 49.39 minutes for admitted and transferred regular patients.

Table 3-25 Hypothesis test on the result of the first experiment

Experiment #5	Regular Patients (Discharged)	Regular Patients (Admitted/ Transferred)	BH crisis Patients (Discharged)	BH crisis Patients (Admitted)	BH crisis Patients (Transferred)
Average	-19.46	-49.39	-103.74	-68.42	5.36
STD DEV	18.57	19.14	165.28	114.47	159.07

Confidence	0.05	0.05	0.05	0.05	0.05
HW	7.67	7.90	68.22	47.25	65.66
UL	-11.79	-41.49	-35.51	-21.17	71.02
LL	-27.12	-57.29	-171.96	-115.67	-60.30
Rejected	X	x	x	X	

With the proposed change,

- For regular patients that are discharged, the LOS will be shortened by 11.79 to 27.12 minutes with an average of 19.46 minutes,
- For admitted or transferred regular patients, the LOS can be shortened by 41.49 to 57.29 minutes with an average of 49.39 minutes,
- For discharged BH crisis patients the reduction is in the range of 35.51 to 171.96 minutes with the average of 103.74 minutes,
- For admitted BH crisis patients the LOS can be reduced by 21.17 to 115.67 minutes with an average of 68.42 minutes,
- For transferred BH crisis patients the LOS can be increased by up to 71.02 minutes or reduced by up to 60.30 minutes with an average reduction of 5.36 minutes.

Chapter 4 Phase II- Detailed Model

To be able to test possible impact of a new process that the ED was planning to implement, further identify bottlenecks and rooms for improvement, a second model simulating the current process was built to include, detailed activities that were modeled simply by the roomed-to-disposition time in the basic model in phase I. Once the “as-is” model was completed, verified and validated, a “to-be” model was built to test the impact of it on the average LOS and rate of LWBS from the changed process. The “to-be” model is called the Joint Evaluation Treatment (JET) that is suggested as a best practice in the literature and considered for implementation by the ED. The aim is to improve patient flow and patient satisfaction through vertical triage. Where patient with lower acuity levels and non-urgent chief complaints will be assessed by a physician or physician assistant (PA) in the JET rooms and wait in a waiting area named “result waiting area (RWA)” after the assessment. This strategy is expected to free up beds and rooms for more urgent patients and make the patients flow faster in the ED.

4.1. Data Collection

To build the detailed model, the roomed-to-disposition time was broken down into major activities including nurse assessment, physician assessments, lab(s), and imaging process(es). Physicians and ED staff were followed on different time of the day for several days to assure the data collected were not biased. Activity time including the time spent by physicians to review the history of the patient, time to do the assessment, time spent to put notes into the computer system and time to order labs and/or images, as well as the number of physician visits needed for each patient were collected. 109 data points were collected and used to generate the physician assessment time distribution, which is shown in Figure 4-1. Data from 130 patients were evaluated to calculate the percentage of patients needing one to four physician visits, as shown in Table 4-1.

Table 4-1 Percentage of number of required physician visit

One Visit	47.2%
Second Visit	38.6%
Third Visit	11.6%
Fourth Visit	2.6%

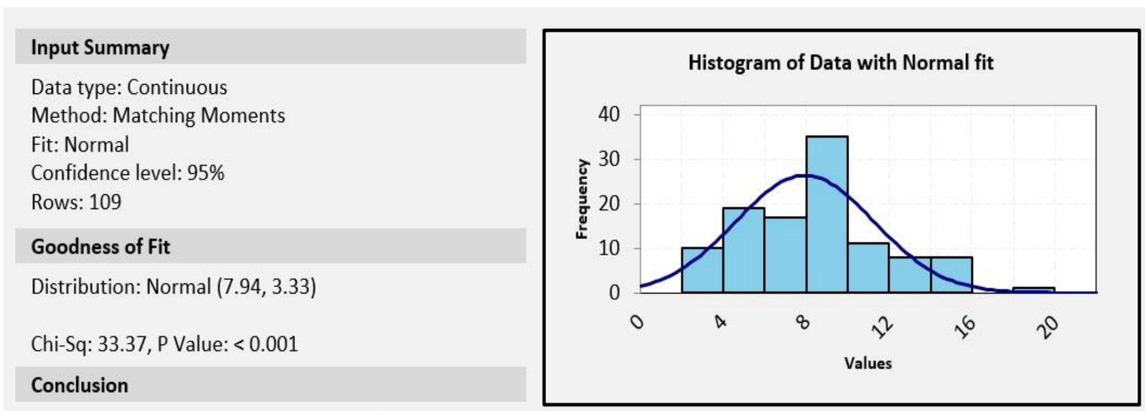


Figure 4-1 Distribution fitted to physician assessment time

The same procedure was followed to record activity times of nurses in the room including assessment time, and the time to cleaning the rooms after a patient leaves. The number of nurses required for different types of patients with different arrival types was also recorded. The ED is divided into 5 different zones and each zone has its own nurse station. Although the nurses are each assigned to a patient in their own zone, they usually cover each other’s tasks when needed. Besides that, in the case of emergency, the charge nurse balances workload among nurses in different zones. Therefore, patient care is barely delayed due to the lack of nurses. Noticing that the activity of nurses was divided into three main activity including initial nurse assessment happening at the patient arrival into the room, EMS arrival triage in the room, and nurse visit after each physician assessment to help patients with their needs such as medicine, IV and etc. Due to the complexity of the system and variety of patient needs, it was hard to differentiate each specific nurse activity time. Therefore data of each nurse visit were collected and one distribution was fitted using the 56 data points collected to generate one distribution for nurse visit time. Figure 4-2 shows the best distribution fitted to the nurse activity data.

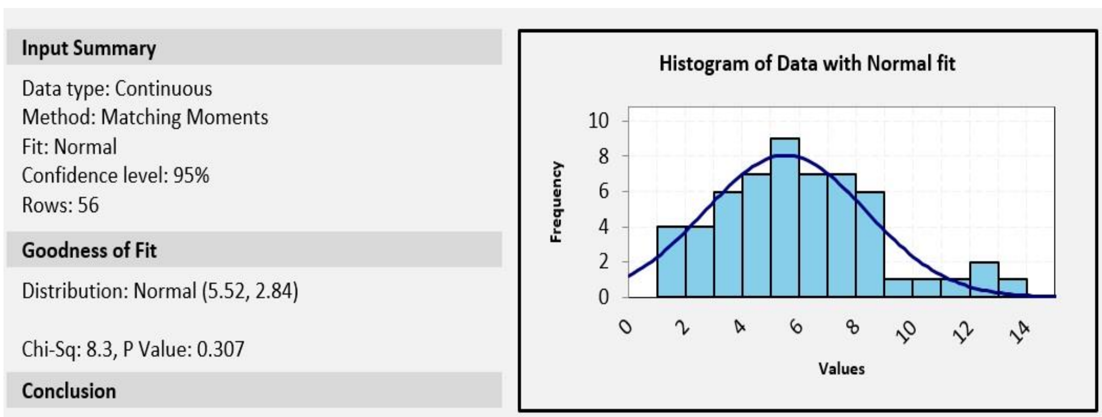


Figure 4-2 Distribution fitted to nurse activity time

The data regarding lab time for a one-month period (July – August 2017) was provided by the hospital IT staffs. The lab time was divided into three portions including lab order-to-lab collect time, lab collected-to-receive time and lab received-to-result time. Lab order-to-collect time starts from the moment that a physician order labs for a patient till the time that samples are collected. Lab collected-to-receive time starts from the time that sample collection is done till the time that the lab receives samples. The lab received-to-result time is from the moment the lab receive samples till the results are posted on the system. Data outliers were found and deleted through a couple of discussions with the experts. Although there are many different types of laboratory exams and each may need a different amount of time to collect the sample and post the results, due to the complexity of the data collection all data regarding labs were aggregated and treated as same. Three distributions were fitted to these three data sets to represent the lab activity times. Figures B-1 to B-6 in the appendix II show the result of autocorrelation test as well as fitted distributions to each data set. The number of labs done for each patient was exported from the patient logs in the ED database provided by the hospital IT staffs. A user distribution was defined to assign the value of a number of labs needed to each entity at the arrival locations.

Likewise, the required data regarding imaging time was provided by the IT staff for the same period of time. The imaging activity time includes image-ordered-to-exam-ended time and image-taken-to-result result time. Image-ordered-to-exam-ended taken time starts from the moment that a physician order images for a patient till the image are taken, while the image-taken-to-result time starts from the moment that imaging is ended till the image results. Data outliers are found and deleted through discussions with the ED staff. The number of images done for each patient was also exported from the patient logs and a user distribution was used to assign an attribute to the patient at the arrival location representing the number of images needed. Two distributions were fitted to data to generate imaging time. Figures B-7 to B-10 in the appendix II result of autocorrelation test as well as fitted distributions to data.

4.2. Data analysis

To deal with the complexity of the care at ED patients can be classified into different groups to be routed and treated differently in the model. Patients may go through different treatment processes, get different resources and have a different priority to receive the service in the ED. In the detailed model, special cases were considered and patients were classified into five special cases and one regular type. Special cases were sepsis, stroke, chest pain, trauma and BH crisis patients. The ED staffs provide patient records of each special case and regular patients for a one-month period (July-August 2017). Two distributions were defined based on the percentage of each special case to assign the special case attribute to each entity at two arrival locations.

Since the BH crisis, patients may use resources from outside of the ED psychiatrists, and their treatment process may vary case by case, modeling the detail of activity in the room was time-consuming and complicated. Therefore, to represent the roomed to disposition time like the basic model a distribution was fitted to the data. Electrocardiography (EKG) is the required resource for the sepsis, stroke, trauma and mostly the chest pain patients. Therefore, the activity time regarding EKG was recorded and it was noted that the process for almost all cases takes 2 minutes to be done. Besides the EKG sepsis, stroke, trauma, and chest pain patients were modeled to have higher priority over regular patients with ESI level of 3,4 and 5 to get into the room.

To add disposition to depart time after finishing the treatment time new distributions are fitted to the one-month period of provided data. Analysis of the data records revealed that regarding disposition to depart time the data can be classified into four groups of discharged regular patients, admitted/transferred regular patients, discharged BH crisis patients and admitted/transferred BH crisis patients. Since the disposition to depart time for all special cases except the BH crisis patients is pretty similar to the regular patients they are all classified as one group. Figure B-11 to B-22 in the appendix show the autocorrelation and fitted distribution on each set of data. Table 4-2 shows fitted distributions to each data set.

Table 4-2 Distributions fitted to disposition to depart time data

Patient Type	Data	Number of data points	Fitted distribution
Admitted/Transferred BH crisis Patients	Roomed to Disposition Time	113	Lognormal (3.76, 6.21, 1.31)
	Disposition to Depart Time	110	Pearson 6(1, 27.7, 6.17, 1.76)
Discharged BH crisis Patients	Roomed to Disposition Time	194	Loglogistic (12, 1.24, 233)
	Disposition to Depart Time	185	Pearson 6(1, 5.36, 3.99, 1.02)
Admitted/Transferred Regular Patients	Disposition to Depart Time	503	Gamma (10, 1.85, 52.2)
Discharged Regular Patients	Disposition to Depart Time	1749	Loglogistic(1,2, 18.4)

4.3. Simulation Modeling

The following assumptions were made:

- Waiting area and all queues do not have limited capacity.
- Rooms at all zones except trauma rooms are not prioritized for patients.
- All patients arriving at walk-in arrival walk into the ED and do not need any nurse to be escorted with.
- Physicians, RNs and Aids stay in main nurse station located in the center of ED when idle.

- All staff can cover the whole ED area and they do not have any specific zone assigned.
- The patient does initial registration at the registration desk and complete registration and payment happen right before discharge. This part was not modeled since it was included in deposition-to-depart time.
- For all patients waiting in the waiting room with the same condition first come first served rule was applied.
- Patients stay in their room for all image and lab activity from order to result time.
- Physicians review results and historical records of patients in the room.
- The triage nurse is not modeled and it is assumed there is always one triage nurse in the room to do the process.

- BH crisis patients who are medically unstable stay in the core ED rooms for further treatment after becoming medically stable.
- There are some other resources working in the ED such as charge nurse, trauma team or stroke team. But since the care is never delayed due to lack of these resources or they may not have a direct impact on the process, in the modeling, they are neglected.

After data collection, the basic model is used as the base to develop the detail model. The entity flow diagram of the detail model is similar to the basic model represented in Figure 3-15, and the description of the operation is similar to what is shown in Table 3-3. The only difference in the process was in the activities happen in the room which was described earlier. Entity, locations, path network, and variables are the same with the base model. Changes are additions are made to the resources and shifts, attributes and user distributions. Like the basic model the only entity flow through the system and exit the system at the end is the patient. Entities are entering the system with the same arrival pattern as the basic model and they are all being differentiated by attributes.

4.3.1. Attributes and user distributions

In addition to the ones in the basic model, some other attributes were added to control the flow of patients in the system. Table 4-3 and 4-4 shows the attributes defined in the detail model.

Table 4-3 Attributes in the Detail Model 1

Attribute	Type	Arrival type	Value	User Distribution	Notes
a_Special_case	Integer	Walk-in	1	89.2%	Regular patient
			2	5.7%	BH crisis
			3	3.5%	Chest pain
			4	0.1%	Sepsis
			5	1.2%	Stroke
			6	0.3%	Trauma
		EMS	1	75.8%	Regular patient
			2	10.4%	BH crisis
			3	6%	Chest pain
			4	2.4%	Sepsis
			5	3%	Stroke
			6	2.4%	Trauma
		LAW	1	0%	Regular patient
			2	100%	BH crisis
			3	0%	Chest pain
			4	0%	Sepsis
			5	0%	Stroke
			6	0%	Trauma
a_Num_of_lab_needed		Walk-in EMS LAW	0	36%	The number of labs required for a patient
			1	17%	
			2	26%	
			3	18%	
			4	3%	
a_Num_of_image_needed			0	49%	The number of images required for a patient
			1	31%	
			2	18%	
			3	2%	
a_Num_of_dr_visit_needed			1	47.2%	The number of physician visits required for a patient
			2	38.6%	
			3	11.6%	
			4	2.6%	

Table 4-4 Attributes in the Detail Model 2

<table>
<tr><th>Attribute</th><th>Type</th><th>Value</th><th>Notes</th></tr>
<tr><td>a_resource_no</td><td rowspan="5">Integer</td><td>1-99</td><td>The index number of a resource assigned to a patient</td></tr>
<tr><td>a_Lab_signed_to_result</td><td>0-1000</td><td>Total lab time from order to result</td></tr>
<tr><td>a_Image_signed_to_result</td><td>0-1000</td><td>Total image time from order to result</td></tr>
<tr><td rowspan="2">a_EKG_done</td><td>0</td><td>If patient has not done EKG</td></tr>
<tr><td>1</td><td>If patient has done EKG</td></tr>
</table>

Among them, “a_Special_case” was divided into six groups of patients including regular, BH crisis, chest pain, sepsis, stroke, and trauma patients. “a_Resource_no” was used to assign a physician to a patient and make sure that the same physician will visit the patient for the following assessments, reviewing results of lab and image and disposition. Three attributes were defined to indicate how many times a physician will visit a patient, and the number of labs, and images required for a patient. These attributes get values at the arrival locations based on the user distribution assigned. “a_Image_signed_to_result” was defined to represent the total time generated by distributions corresponding the image process from order time to result, while “a_Lab_signed_to_result” was used to represent the total time generated by distributions to represent the lab process from order to result in time. These two attributes were defined to help in the situation where both lab and image are ordered are ordered. The model uses two attributes to make sure the waiting time is an overlap of the time to wait for lab and image results. In these situations, the two attributes were compared to find which one takes longer and the patient will wait for that amount of time.

"a_Hall" was defined to differentiate patients in the hallway bed from the ones waiting in the waiting room, so they can get a higher priority to get into a room. "a_EKG_done" was defined to differentiate patients who have done EKG from those who have not.

4.3.2. Resources and shifts

In addition to the basic model resources, three physicians and an EKG unit were added to the model. Physicians were assigned by the first available rule to patients. However, physicians were modeled to visit the patient who they are assigned to till the discharged time. All of the resources were set to return to their station when idle. Table 4-5 shows the resources defined in the basic model.

Table 4-5 Resources in The Detail Model

Resources built in the model	Resources in the ED	Number of staff
RN	Register nurse	25
Aids	Nurse aids	10
Dr	Physician	3
EKG_Unit	EKG	1

4.4. Modeling Logic

In the detailed model, the processes from the patient arrival to triage is the same with the basic model and same distributions were used to generate the registration and triage time.

Regular patients arriving at walk-in arrival were routed either to the room or to the waiting room based on their ESI level after they leave the triage room. Patients of ESI level 1 and 2 are directly routed to the rooms or hallway beds if all rooms are full. Patient with ESI level 3,4 and 5 are directed to the waiting room if they are adults or to the pediatric waiting area if they are children. Those who cannot wait in the waiting room identified by an attribute were routed to the hallway beds in the ED. Patients on the hallway bed have a higher priority than those in the waiting room with the same health condition to get into a room. From the waiting room patients with ESI level, 4 and 5 were routed to the fast-track rooms and then to the “FT_waiting” area. Patients with ESI level 3 were routed to the blue, red, yellow zone. If none of the room is available they will wait in the “RP_waiting” area for a room to become available. The Same logic was used for the pediatric patients waiting in the “Pedi_waiting” area. The routing priority for the patient with same special case attribute and ESI level in the waiting room is first in first out. The RNs and Aids escort the patient with the longest waiting time from the waiting room to the room. For all regular patient, room number 1, 2, 11 and 12 have the lowest priority as they are mostly reserved for the most urgent conditions and some special cases, such as trauma.

Medically stable BH crisis patients arriving at EMS/LAW arrival were routed to purple zone rooms. They were modeled to go into fast-track rooms in case that all purple zone rooms were full. Unstable EMS/LAW arrival BH crisis patients were directed to the rooms in blue, red and yellow zone rooms. For BH crisis patients in the purple zone, a distribution was used to generate the roomed to disposition time.

Chest pain patients arriving at walk-in arrival were routed to core ED rooms after triage. EKG bay is the backup room for these patients to go there and perform the EKG is no rooms is available. In the EKG bay, the attribute “a_EKG_done” that indicate if a patient has done the EKG, will be changed to 1 so that the patient will not get an EKG in the room.

However, chest pain patients arriving by ambulances get the value for “a_EKG_done” attribute, since they do the EKG in the ambulance.

Sepsis and stroke patients have higher priority to be routed to the room 1, 2, 11 and 12. They can go to blue and red zone rooms too, but not preferred which was modeled as a lower priority in the routing. They have hallway beds as a backup in case all rooms are full. Trauma patients can only go to the room 1,2, 11 and 12 and they have the hallway beds as backups. The routing scheme for both EMS/LAW arrival and walk-in patients for sepsis, stroke and trauma case is same. All patients were modeled to be taken to the rooms, hallway beds or EKG bay by RNs or Aids in the ED. The following code shows how routing patients were modeled.

```
1: Inc v_Num_in_triage_to_room_q /*increase value of variable shows the number of patients waiting to get
triaged*/
2: If Special_case=3 /*Chest pain case*/ Then {Graphic 1 Route 3 /* All rooms (blue and red rooms have higher
priority) and EKG bay as backup */ }
3: If Special_case=2 /*BH Crisis patients*/ Then
{Graphic 2
4: if Rand(100)> 20 Then Route 4 /*medically stable go to Purple zone and Fast-track rooms as backup*/ Else
Route 7 /* Medically Unstable go to Blue, red and yellow */}
5: If Special_case=6 Then { Graphic 3 Route 5 /*Trauma rooms B1,R2,B11,B12 and Hallway beds*/}
6: If Special_case=4 /*sepsis patients*/ Or Special_case=5 /*stroke case*/Then {Graphic 4 Route 6 /*Blue and
red zone rooms and hallway beds*/}
7: If Special_case=1  /*Regular patients */ Then
{Graphic 5
8: If ESI <= 2 Then Route 8 /*Red, blue, Yellow zone rooms and Hallway beds as backup*/
9: Else {If a_need_hall_way = 1 Then Route 8 /*ESI level 3,4 and 5 who cannot wait in the waiting room Red,
blue, yellow zone and Hallway beds*/
      Else
         {If a_Adult=1 then Route 1 /*waiting area */ Else {Graphic 6 Route 2 /*Pediatric waiting area */}}
      }
}
```

In all rooms except purple zone rooms, the treatment process starts with the initial nurse assessment. Patients with ESI level 1 and 2, Sepsis, Stroke, Trauma get two nurses for the initial assessment. EMS arrival patients also get two nurses, one to do triage and one to do the initial assessment. Fast-track patients and patient with ESI level 3 get one nurse for the initial assessment. The treatment process was followed by a physician visit in the model. Physicians were assigned to the patients by first resource available rule. The first physician assessment includes the patient history review of the patient time and the distribution time defined for the physician assessment. After physician assessment lab, images or both may be ordered. In the reality lab when a physician order a lab, patient wait in the room for a lab technician to come and take samples. Lab technician takes the sample to the laboratory and results will be posted on the patient profiled to be reviewed by the physician who orders the lab. For ordered images, based on the type of imaging the patient may be taken to the imaging locations, or wait in the room for imaging technician to come and do the exam in the room. There are three possible scenarios. The patient needs just lab, the patient needs just image and patient needs both image and lab. For the modeling purposes, patients are modeled to wait for the total time of lab or image process from order to result in time in the room. After each lab or image, the assigned physician reviews the result. In reality, this activity can happen in the physician station or in the physician office, however, for the modeling purposes, the physician reviews the result in the patient room. A triangular distribution was fitted to the collected data to represent the review lab and image results required time. If a patient needs more than one-time assessment, the physician will go to the room and do the assessment again, and labs or images may be ordered again. Between physician assessments of a patient, an RN visit was modeled. The process was repeated till all required labs, images and assessments finish. To model, all activities described a macro was used to apply to all rooms. The treatment process for different patients was differentiated by using attributes. Following is part of the code in macro including first nurse assessment, physician assessment, first image and lab activity. IF condition was used to calculate total activity time for lab and or image to be done.

```
1: Log "Triage to roomed”, a_triage_time /*to record the triage to roomed time*/
2: If a_Special_case=1 /*regular patients*/ Then
3: {If a_ESI>1 and a_Arrivaltype<>2 then Use 1 RN For N(5.2,2.9) /*first nurse assessment Walk-ins law*/ Else
Use 2 RN For N(5.2,2.9) /*first nurse assessment for EMS arrivals*/
4: Get 1 DR
5: wait N(7.61, 3.63)+2 /*first Doctor assessment and put order*/
6: a_Resource_no=Res (OwnedResource()) /*return the index value of the doctor assigned to the patients*/
7: Free All}
8: If a_Num_of_lab_needed>0 and a_Num_of_img_needed>0 Then /*first lab and first Image*/
9: {a_Lab_signed_to_result=T(1,4.2,45) + T(1,3.5,15) + (16*(1./(1.-U(0.5,0.5)))**(1./2.2)) /*signed to
collect, collect to receive, receive to result for lab time*/
10: a_Image_signed_to_result=T(9, 25, 125) + 10+E(31.6)/*signed to collect, collect to receive, receive to
result for image time*/
11: If a_Lab_signed_to_result>a_Image_signed_to_result Then Wait a_Lab_signed_to_result Else Wait
a_Image_signed_to_result /*solve the overlap of time issue*/
12: Get res(a_Resource_no) /*assigned physician will come to review image and lab result*/
13: Wait T(2,5,10) /*review lab and image results*/
14: Free res(a_Resource_no)}
15: If a_Num_of_lab_needed>0 And a_Num_of_img_needed=0 Then /*first lab*/
16: {a_Lab_signed_to_result=T(1,4.2,45) + T(1,3.5,15) + 16*(1./(1.-U(0.5,0.5)))**(1./2.2)
17: Wait A_Lab_signed_to_result /*wait for lab to be done*/
18: Get res(a_Resource_no)
19: Wait T(1,2.5,5) /*review lab or image results*/
20: Free res(a_Resource_no) }
21: if A_Num_of_lab_needed=0 And A_Num_of_img_needed>0 then /*first image*/
```

```
22: {A_Image_signed_to_result=T(9, 25, 125) + 10+E(31.6)/*signed to collect, collect to receive, receive to
result image time*/
23: Get res(a_Resource_no)
24: Wait T(1,2.5,5) /*review lab or image results*/
25: Free res(a_Resource_no)}
```

Patients wait for the disposition to depart time generated from the defined distributions for each type. The patient leaves the ED after completion of disposition to depart time whether they are discharged, admitted or transferred. The occupied room is closed for cleaning purposes right after that. The cleaning time was generated by a triangular distribution with 5, 7 and 15 as parameters.

4.5. Verification and Validation

Since the most part of the detail, the model is similar to the basic model and had been verified before in the detail model the activity in the room was reviewed by the experts. The whole process from the patient arrival till departure for all different groups of patients with the different special case, disposition type, ESI level and arrival type was presented to hospital administrators to verify the model. The final detail model was simulated with a focus on ensuring that the model works as expected. A one-week was set up for the model as the warm-up time, and it was simulated for 25 replications of one-month period. The model is validated by the comparison of the simulation result to the actual data illustrated in Table 4-6.

Table 4-6 4)

	Average length of stay	
	Actual	**Detail Model**
Discharged regular patients	212	211
Admitted/transferred regular patients	301	282
Admitted/transferred BH crisis patients	1061	1087
Discharged BH crisis patients	856	903

4.6. Experiments

After verification and validation of the detail model, since the hospital manager wanted to test the impact of implementing JET on the average LOS, patient waiting time and a total number of patient, the detail model was modified. A couple of sessions with physicians and hospital administrators were placed to clarify the JET process and how it is going to be implemented. Changes in current resources and locations were reviewed to have a better understanding required for the modeling. Besides the impact of the JET improvement plan on the average LOS and patient waiting time, the hospital administrators wanted to test different scenarios of patient routing. Therefore, after building the JET model three scenarios which will be described later were tested and the results were presented to the managers.

4.6.1. The JET Model

At the moment of this study, the JET was not implemented in the ED and the outcome of this part of the study was to show the hospital managers how it would affect the average LOS and patient waiting time. Therefore, in the JET model, similar distributions to the detail model were used to generate time of each activity except for the triage time. Since in the JET the triage time was supposed to reduce in half, the parameters of the triangular distribution for the triage time were changed to 1, 2 and 7.5 as the lower limit, most likely, and upper limit respectively. The main difference between JET model and the detail model is in the process within the ED. The outcome of the discussion with the experts regarding the flow of patients in the system and required resources for each activity were the following entity flow diagram accompanied with the table of the description of operation. Figure 4-3 is showing the entity flow diagram of the JET model while the description of operations is shown in Table 4-7.

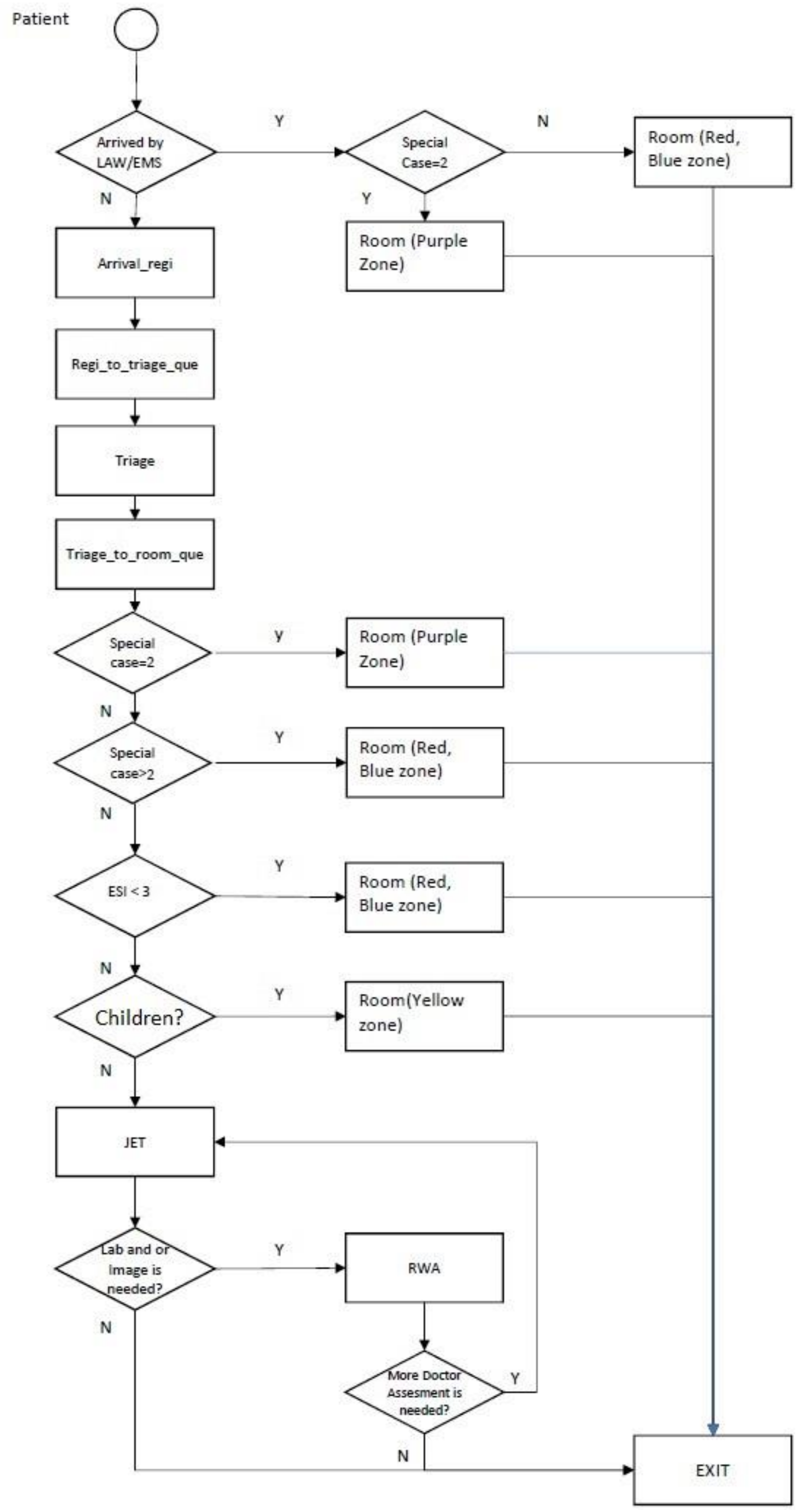


Figure 4-3 Entity Flow Diagram of The JET Model

Table 4-7 Description of Operation in The JET Model

Location	Activity Time	Next Location	Move Trigger	Move Time	Move Resource
Arrival	None	Arrival_reg	Walk-in arrivals		None
		Room	EMS or LAW arrivals		Aids/RN
Arrival_reg	U (3.5, 1.5)	Regi_to_triage_que	None	0.5min	None
Regi_to_triage_que	None	Triage	When triage is available		None
Triage	T (1, 2, 7.5)	Triage_to_room_que	None		None
Triage_to_room_que	None	Room (Purple zone)	Special case=2 (BH patient)		Aids/RN
		Room (Red and Blue zone)	Special Case>2		Aids/RN
		Room (Red and Blue zone)	ESI<3		Aids/RN
		Room (Yellow zone)	Adult=0 (Pediatric Patients)		Aids/RN
		JET (FT1-4 and room 5 and 6 in red zone)	ESI>=3		Aids/RN
JET	Physician assessment, Nurse assessment, Lab and Image activity	RWA	Lab or Image is needed		Aids/RN
		Exit	No more Lab or Image is needed		Aids/RN
RWA	Waiting for Lab and or Image results	JET	More doctor assessment is needed		Aids/RN
		Exit	No more doctor visit is needed.		Aids/RN
Room	Physician assessment, Nurse assessment, Lab and Image activity	Exit			

In the JET model after triage, patients were routed differently. All special case patients except unstable BH crisis patients were routed to the core ED rooms in the red and blue zone and to the hallway beds as a backup, while BH crisis patients were routed to the purple zone rooms with the core ED rooms as backup. Regular patients with ESI level of 1 and 2 were routed to the red and blue zone rooms. In case that all rooms are occupied, they can go to the hallway beds. Patient with ESI level of 4 and 5 was directed to the JET rooms. The JET area includes fast-track rooms and rooms 5 and 6 in the red zone. Among patients with ESI level 3, there is a certain percentage that are unstable or having abnormal vitals and or need IV medicine, and they were routed to the red, blue or yellow zone rooms. Since the JET was not implemented at the moment of this study, the data of ESI level 3 patients with the unstable condition, signs of abnormal vitals or need for IV meds were collected in the current system. Based on the collected data of 47 patients, 72 percent had these conditions and had to be room in the red, blue or yellow zone rooms and the rest can be seen in the JET. Pediatric patients with ESI level of 1 and 2 were routed to the red and blue zone rooms, while ESI level 3,4 and 5 were directed to the yellow zone rooms to be visited by a pediatric physician.

For the patients in the red, blue and yellow zone the treatment process was modeled similar to the detail model, however, for patients in the JET area, the process is different. In the JET rooms, patients were modeled to be assessed by a nurse and a physician. If a patient needs a lab or image to be done, they start it in the room and they wait for the result in the result waiting for the area (RWA). In the case of more required physician visits, the patient was routed to go back to the JET room. If there was no lab or image ordered for the patient, he or she was discharged from the JET room directly, otherwise, it was modeled to be discharged from the RWA. In addition to the attributes used in the detailed model three new attributes were added to the model. “a_Num_of_image_done” to compare number of imaging process that patient has been going through to the number of imaging were needed. “a_Num_of_lab_done” used in the same way for number of labs. “a_Jet_visited” is an attribute which was used for patients who were visited in the JET area and were routed to the core ED room. This attribute skip the initial evaluation since in the real case the physicians are not evaluating patients who are already been evaluated in the JET area.

Regarding the model components, in the JET model, part of the current waiting area was renamed to RWA, where JET patients can wait for the result. In addition, one pediatric physician named “Ped_dr” was added to the model to only visit the pediatric patients in the yellow zone and one of the physicians was assigned to visit JET physician named “Jet_dr” in the model. The JET physician can also visit the patients in other zones in case of need. A physician assistant (PA) was added to the model who can only assess JET patients. Since the hospital administrators wanted to test the different scenarios of sending JET patients to the red, blue and yellow zones, a new attribute named “a_Jet_visited” were added to get value when a patient is visited by a physician in the JET. In this case when a JET patient is routed from the JET to the rooms in the other zones, won’t get an additional visit. The following code was used in the room macro to ensure that for these patients just a new physician is going to be assigned and no extra visit would happen. Following is a part of code used to model activates in the JET rooms.

```
if a_Jet_visited>0 then goto L42 /* Skip the initial evaluation */
Use 1 RN For N(5.2,2.9) /* first nurse assessment*/
Get 1 PA Or Jet_Dr /* first assessment by a PA or JET_Dr */
Wait N(7.61, 3.63) /*first Dr evaluation time*/
a_Resource_no=Res (OwnedResource()) /* to make sure patient will be visited by the same Dr again*/
a_Jet_visited=1 /* To skip the first evaluation when a patient return to the room*/
Free all
If A_Num_of_lab_needed=0 and A_Num_of_img_needed=0 Then /* check the required number of labs and images*/
    {If A_Num_of_Dr_visit_needed>1 then {
    Get res(a_Resource_no)
    Wait N(7.61, 3.63) /*second Dr assessment*/
    free res(a_Resource_no)
    Use 1 RN For N(5.2,2.9) /*second nurse visit*/
    If A_Num_of_Dr_visit_needed>2 then
    Get res(a_Resource_no)
    Wait N(7.61, 3.63) /*second Dr assessment*/
    free res(a_Resource_no)
    Use 1 RN For N(5.2,2.9) /*second nurse visit*/      }
    Wait 10+G(1.85, 52.2) /*wait for disposition-to-depart time*/
    Log "Dispo to depart time for regular admitted/transferred patients", a_Dispo_time /*record disposition time*/
    Log "Length of stay for admitted/transferred regular patients", a_Starting_time /*record LOS*/
    Route 1 */Exit the system*/
   if A_Num_of_lab_needed>A_num_of_lab_done then wait T(1,4.2,45) /*wait for lab to be drawn*/
   Route 3 /*send patient to RWA to wait for the results*/
```

As the only assumptions made in the absence of data, is the percentage of patients going to core ED rooms from JET, was tested in three scenarios to test the sensitivity of this assumption. In the scenarios 1, 2 and 3, 20%, 15% and 10% JET patients were routed to the rooms in red, blue and yellow zone rooms after the first physician assessment in JET. The three scenarios were simulated with a one-week warm-up time and ran for 25 replications. The experiments showed very similar model results which indicates that as long as this percentage ranges from 10% to 20%, the model should behave similarly. Hypothesis tests were conducted using each scenario and they are shown as:

JET model routing 20 percent of JET patients to red, blue and yellow zone rooms

The JET model was simulated for 25 replications. Table 4-8 shows the comparison of triage to roomed value (in minutes) in the JET model versus the detail model. The result shows the 60.5 percent reduction in the patient waiting time. It shows the huge reduction in the waiting time which will decrease the number of patients leaving the ED due to the long waiting time. Table 4-9 Shows the comparison of the average LOS in the JET model versus the detail model. The results show about 14 percent reduction for the admitted or transferred regular patients and 8.1 percent for discharged regular patients. Although the BH crisis patients are being treated in the purple zone and the time was generated by same distributions in both models but since unstable BH crisis patients were treated in the red and blue zones, the better flow of patients in these rooms can improve the average LOS for this group of patients as well. The results show 12.5 and 18.1 percent of reduction for admitted/transferred and discharged BH crisis patients respectively.

Table 4-8 Sensitivity tests on Triage-to-roomed time comparison for all three scenarios

	Waiting time / Triage to roomed time (minutes)			
All Patients	**Baseline**	**10%**	**15%**	**20%**
	38	15	15	15

Table 4-9 Sensitivity tests on Length of Stay Comparison for all three scenarios

	LOS (minutes)			
	Baseline	**10%**	**15%**	**20%**
Discharged regular patients	217	194	193	192
Admitted/transferred regular patients	282	242	240	239
Admitted/transferred BH crisis patients	1087	951	913	924
Discharged BH crisis patients	903	740	716	731

From this point on, the JET model used is the one that assumes 15% JET patients going to core ED rooms since 15% is in the middle of the range and it also generated the best performance. Next, based on this JET model, hypothesis tests with a confidence level of 95 percent were conducted with 25 replications. The first test is as follows:

H0: Implementing Jet will not improve the patient flow in terms of length of stay

H1: Implementing Jet will not improve the patient flow in terms of length of stay

Results presented in Table 4-10 shows that at 95% confidence level, the null hypothesis is rejected for all group of patients. This means that implementation of JET can improve the LOS of all groups. For example, for regular patients that are discharged, the LOS will be shortened by 13.73 to 23.04 with the average of 18.38 minutes. The LOS of discharged BH crisis patients can be reduced by 17.68 t0 300.20 minutes by the average of 158.94

Table 4-10 The hypothesis test result on average LOS of the first scenario

Scenario 1	Regular Patients (Discharged)	Regular Patients (Admitted/ Transferred)	BH crisis Patients (Discharged)	BH crisis Patients (Admitted/ Transferred)
Average	-18.38	-40.55	-158.94	-167.89
STD DEV	11.27	11.21	342.21	369.16
Confidence	0.05	0.05	0.05	0.05
HW	4.65	4.63	141.26	152.38
UL	-13.73	-35.93	-17.68	-15.51
LL	-23.04	-45.18	-300.20	-320.27
Rejected	X	X	x	x

The second test is on the patient waiting time (triage to roomed time) with a confidence level of 95 percent and conducted for 25 replications of three scenarios.

H0: Implementing Jet will not improve the patient waiting time

H1: Implementing Jet will improve the patient waiting time

The result presented in Table 4-11 shows that at 95% confidence level, the null hypothesis is rejected in all scenarios. This means that implementing JET can improve the patient waiting time in all scenarios. The reduction is almost in the same level for all scenarios. For example, in scenario 1 the patient waiting time can be shortened by 12 to 32 minutes by the average 22.05 minutes.

Table 4-11 The Hypothesis Test Result on the patient waiting time (Triage-to-roomed time)

	Scenario 1	Scenario 2	Scenario 3
Average	-22.05	-24.03	-21.72
STD DEV	24.09302	22.50	29.71881
Confidence	0.05	0.05	0.05

HW	9.945108	9.29	12.26732
UL	-12	-14.74	-9
LL	-32	-33.32	-34
Rejected	X	X	X

Chapter 5 Conclusion

In this thesis, discrete event simulation was employed to build valid models for the ED at a local hospital to study its current process and test impacts of possible changes. The modeling part was done in two phases, from building a simple and general model to a complex and detailed one. Both models were verified and validated on performance parameters using multiple ways and complied with actual data. Modeling in phase I was focused to test experiment that can improve the bottlenecks suspected by the ED staffs. Experiments show different degrees of improvement if process at the bottleneck locations could be improved. In phase II, for an in-depth analysis, a detailed model was built that detailed to the level of room activities in the ED. The desired "to-be" model named JET was built to compare the outcome and show how it could improve length of stay and patient waiting time. Initial results showed that implementing JET can reduce the length of stay significantly with a corresponding significant reduction in patient waiting time. Later, different scenarios were tested by modifying the "to-be" model to find the one which has better results in reducing length of stay as well as patient waiting time.

There were some limitations in this study especially due to the absence of data. As an example, there is a different type of imaging and lab that each may take a different amount of time to be completed and resulted. However due to the lack of data in this study, all imaging and labs are treated as the same. Providing data on the different types of imaging and lab and their associated time may improve the accuracy of the model. Since special cases like sepsis, stroke, chest pain and trauma patients are less than 10 percent of all ED patients, the results are pretty accurate. Future studies could acquire data on image and lab correlated to special case patients to further improve the outcome of the model. For example, for many of sepsis cases, a CT scan is required. Differentiated data on this type of imaging may be helpful.

Another limitation in this study was human error. Human error had two impacts on this study, one was in the data when staff or physician may forget to hit the button on the right time to record the time or mistakenly input the wrong data in the system. In this study, most of these data points were found through discussions and data analysis and treated as outliers. Another human error was in the system when a physician forgets to disposition a patient due to the overcrowdedness of the ED. This was not considered in the simulation model though it exists in reality and may affect the patient flow. Future studies can look into those things.

A lot of the future work recommendation observed in the literature on healthcare simulation, included analysis of data. In this study, also there are still a great deal of opportunities in further data analysis. In this study simulation models were built and validated by using two months data provided by hospital. Obtaining more data of the patients can lead the future studies to model the system by using more accurate data and also considering seasonal factor on patient arrival pattern. Defining pattern of patient arrival dependent to the month and season may make to model more accurate and reliable. This can allow the hospital administrators to test scenarios and decision depended to the time of the year. One part which was not modeled in detail in this study was the treatment process in the purple zone. This part was ignored due to lack of data and also because the resources from outside the ED are involved. Besides that, from observation and discussion with a physician, it was noted that time a physician spends on BH crisis patient depends on physician's workload. Whenever they do not have many patients to visit they may spend more time with the BH crisis patient. So, the required assessment time could not be collected easy. Providing more accurate data on the assessment time required for BH crisis patients may improve the results too.

In this work, ESI level was not correlated to the disposition type of the patient. But later in the "to-be" model it was noticed that this correlation can help tracking the patient in the JET system and have a better analysis on the system outcome. It can be suggested that future research look into detail of this correlation and improve the accuracy of the model. Besides that, in this study as it mentioned earlier the ProModel software was used. One of the disadvantages is it does not support multi-processor CPUs, therefore running complex model will take a long time compared to new simulation software packages. Moreover, ProModel does not have any 3D feature and graphical model construction. Modeling in other simulation software that support 3D can be helpful for visualization of the model.

Improving patient flow at ED is an extensive project and could involve the entire hospital. However, the scope of this thesis was limited to looking at ED. A great amount of time was spent on collecting the right data from different sources to be used as an input in the simulation model. Obtaining data in a usable format can improve the accuracy and make the simulation modeling of a complex system like a health care system easier. In this study in the phase I a lot of time spent on making the data usable, since the provided data was not in a good format. In phase II better data were provided based on the requested format and that improved the accuracy and speed of the simulation modeling. In addition to that in modeling a system, certain assumption can have a big impact on the outcome, for example in phase I model BH crisis patients were routed to the dummy waiting location which was reduced the impact of improvement scenarios. Although observation of system can improve the accuracy of the model but there is certain type of information that cannot be covered by observation. Therefore, during the model building effort discussion with people and experts was helpful to have a better understanding of the system. Gathering proper data and focusing on accurate analyzing of it was helpful to build a valid model that mimic the system accurately in all aspects. Simulation models were verified and validated on performance parameters with the actual data and also by presenting it to the ED staff. The first phase of modeling was focused to test improvement scenarios on the known bottleneck in the system. Therefore, the detail activities were not modeled, and two main portions of time were used to represent the treatment time in the room which were roomed-to-disposition time and disposition-to-depart time. Results proved that the waiting time can be shortened up to 33 percent by shortening disposition-to-depart time for admitted and transferred regular patients. It can also reduce the LOS for the admitted and transferred patients up to about 25 percent. Other experiments were performed to show the impact of shortening roomed-to-disposition time for BH crisis patients on the system, and the result proved that the waiting time can be reduced by up to 24 percent while the LOS for discharged BH crisis patients can be shortened up to 40 percent or 376 minutes. In addition, from the reviewed literature, one of the suggested best practices was tested. The result showed great improvement in waiting time which can lower the rate of LWBS. Later in phase II, an in-depth analysis and a detailed model was built. In the detailed model activities such as nurse and physician assessments, lab and image processes were modeled and patients are classified into different groups based on their arrival type, age, acuity level and diagnosis. Different groups of patients were treated differently in the system. The desired “to-be” model named JET was built to compare the outcome with the detailed model and to show how it could improve length of stay and patient waiting time. Initial results showed that implementing JET can reduce the length of stay significantly with a corresponding significant reduction in patient waiting time. Different scenarios were tested by modifying the “to-be” model to find the one which has better results in reducing length of stay as well as patient waiting time. The results showed that by sending 15 percent of the JET patients to the core ED room we can reduce about 14 percent of the average LOS in all groups.

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A. Appendix I

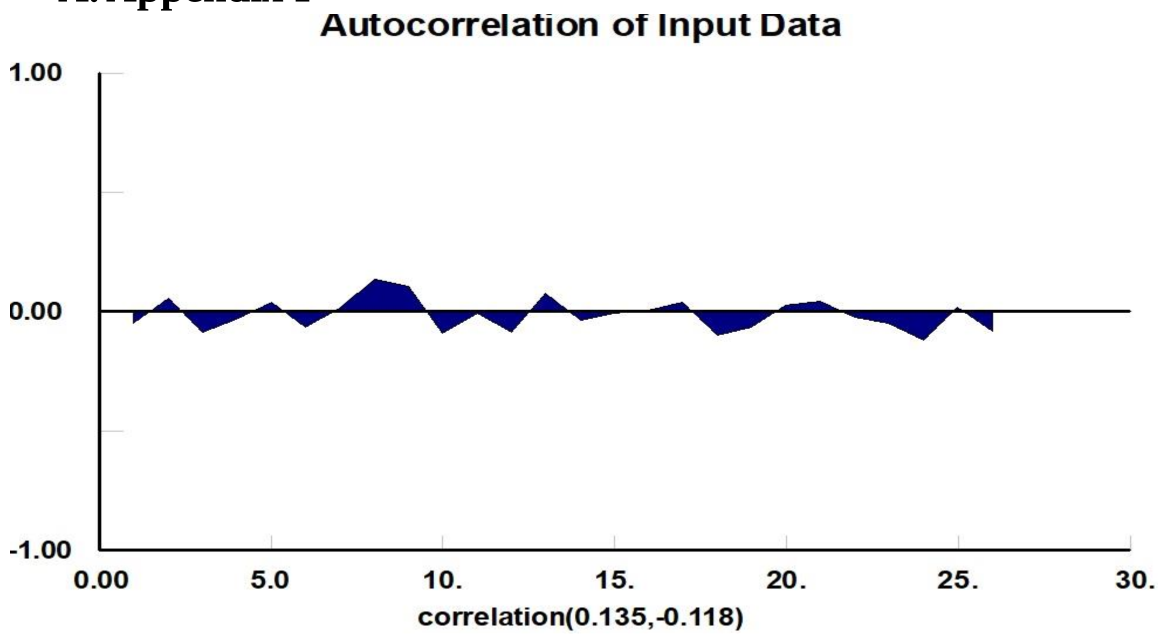

Figure A-1 Autocorrelation test on admitted BH crisis patient roomed-to-disposition time

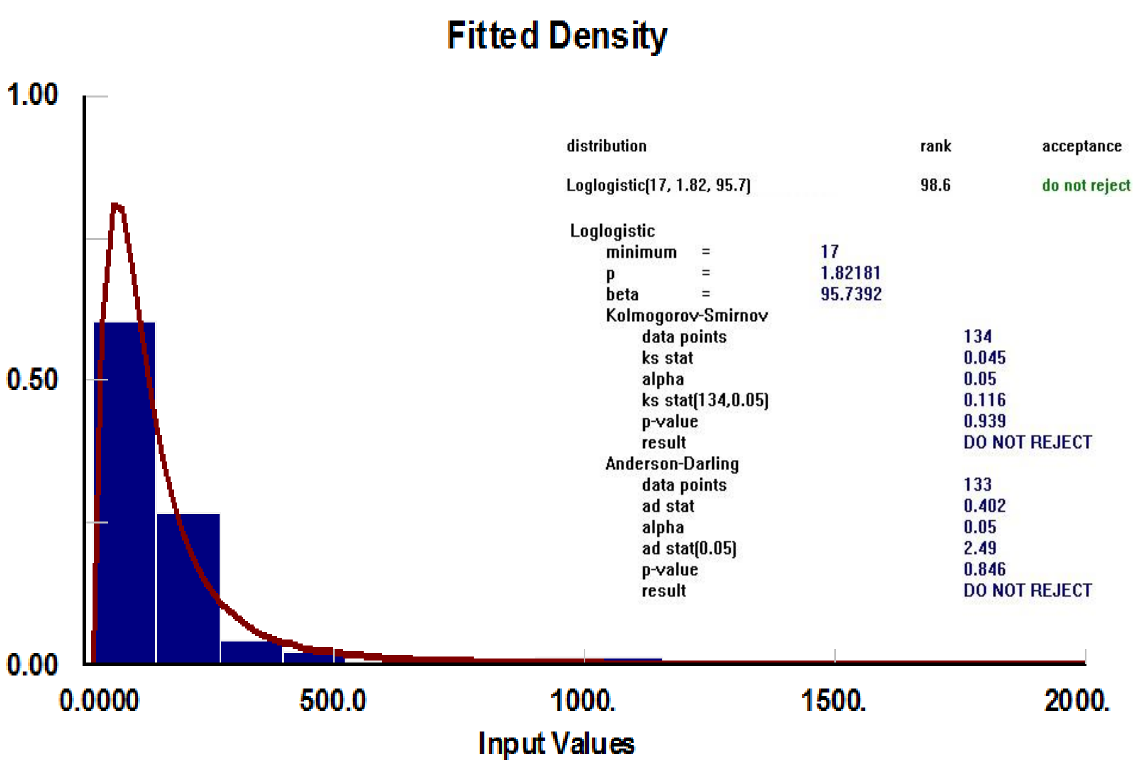

Figure A-2 Fitted distribution to admitted BH crisis patients roomed-to-disposition time

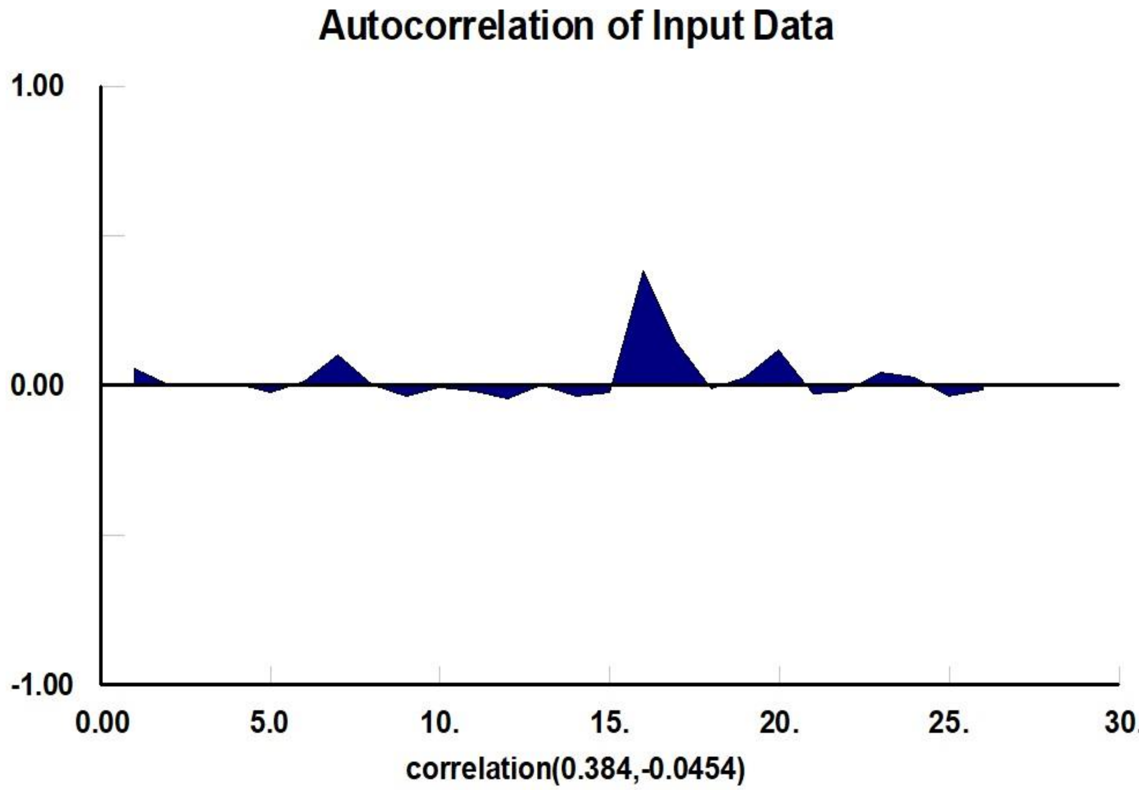

Figure A-3 Autocorrelation test on admitted BH crisis patient disposition-to-depart time

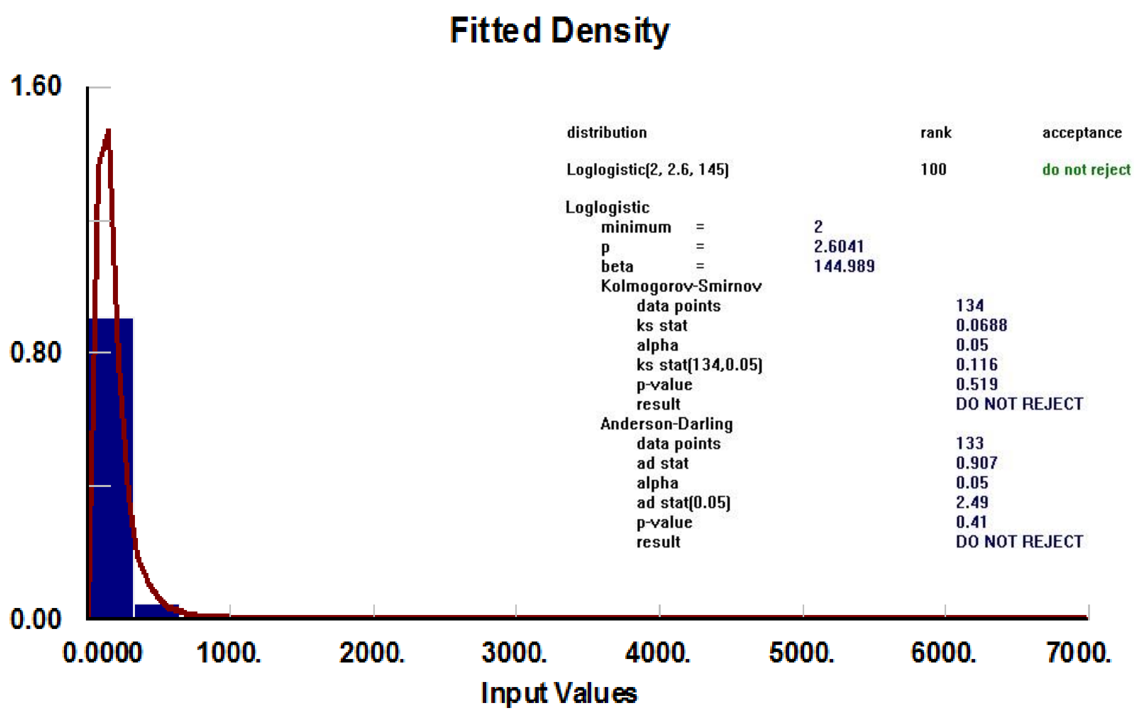

Figure A-4 Fitted distribution to admitted BH crisis patient disposition-to-depart time

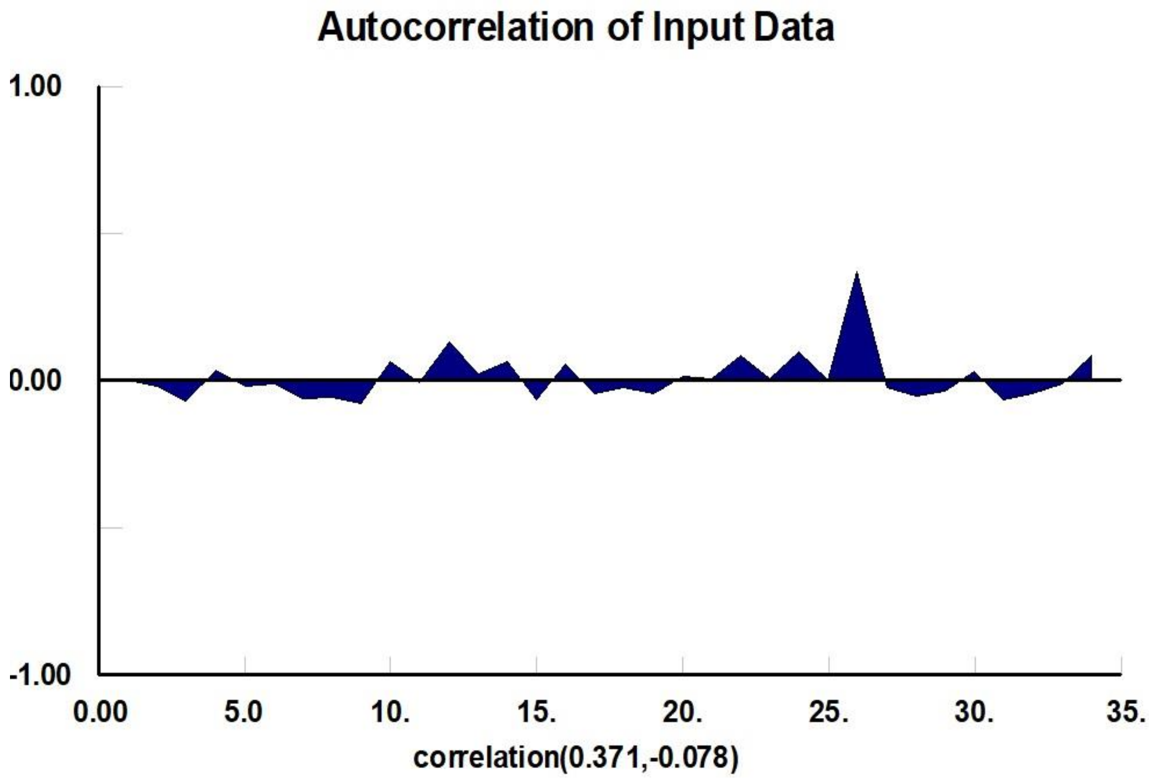

Figure A-5 Autocorrelation test on transferred BH crisis patient roomed-to-disposition time

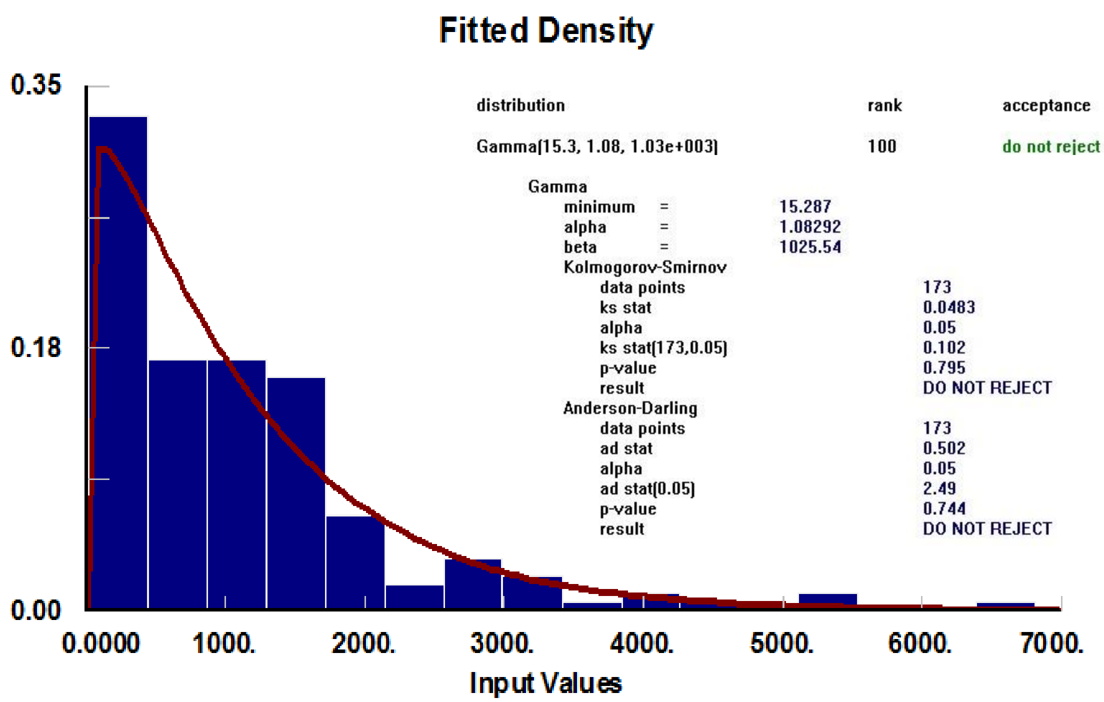

Figure A-6 Fitted distribution to transferred BH crisis patient roomed-to-disposition time

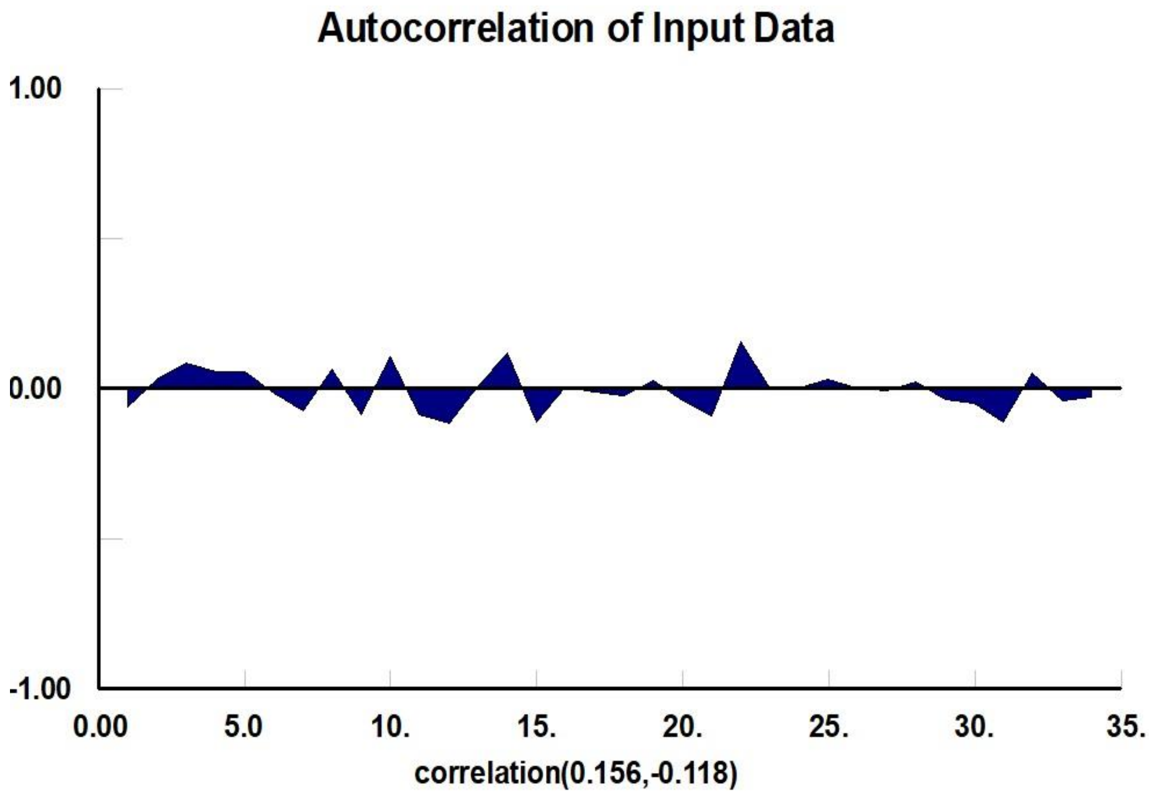

Figure A-7 Autocorrelation on transferred BH crisis patient disposition-to-depart time

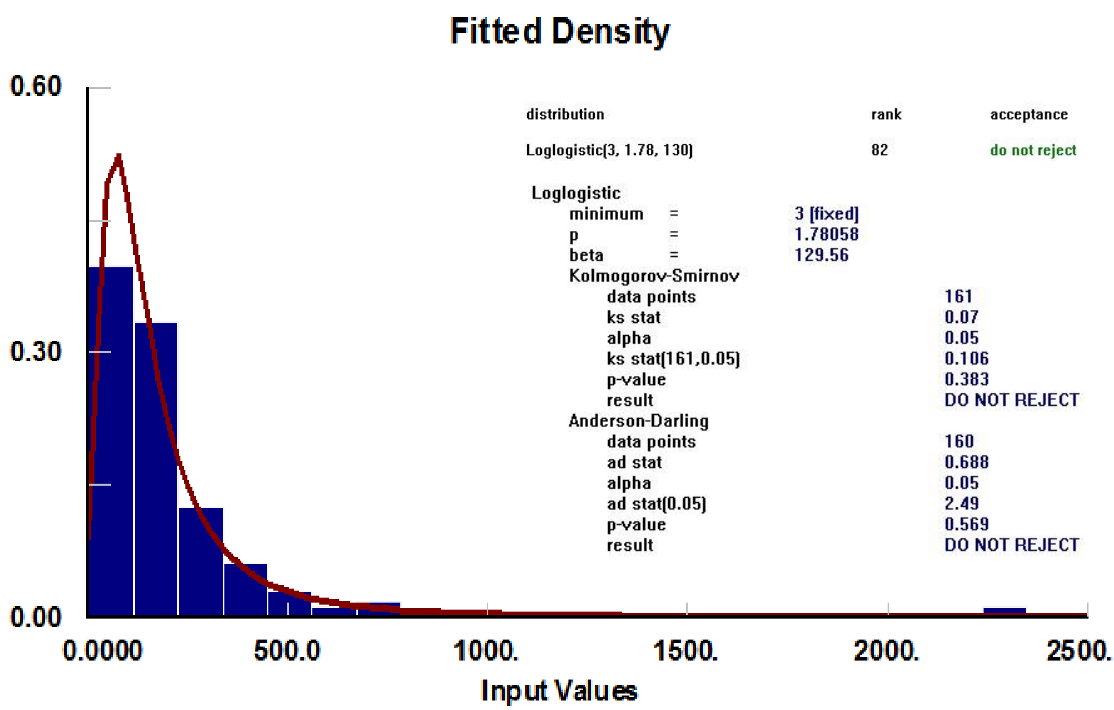

Figure A-8 Fitted distribution to transferred BH crisis patient disposition to depart time

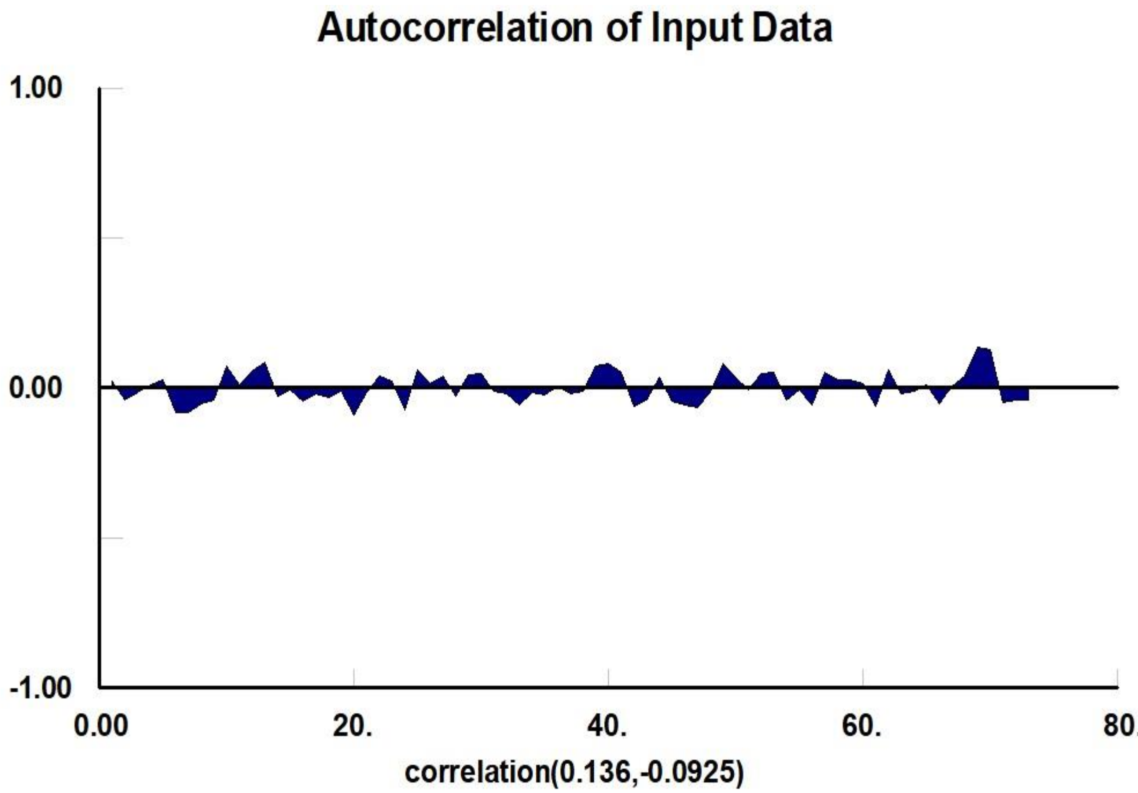

Figure A-9 Autocorrelation test on discharged BH crisis patients roomed-to-disposition time

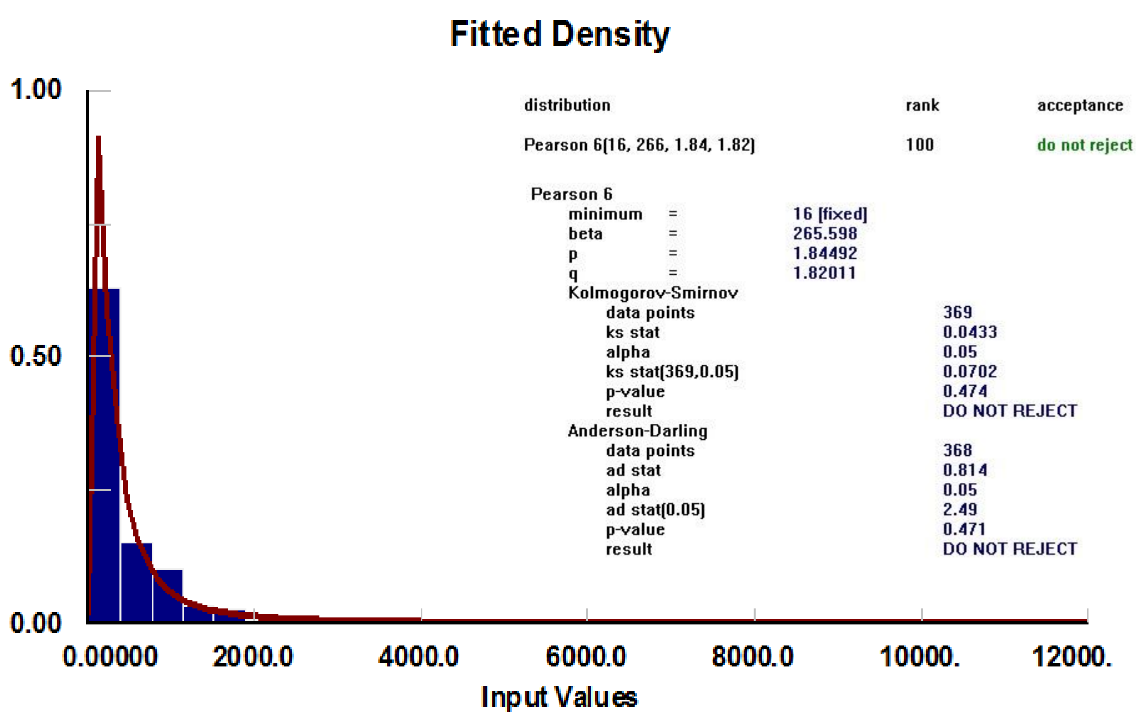

Figure A-10 Fitted distribution to discharged BH crisis patient roomed-to-disposition time

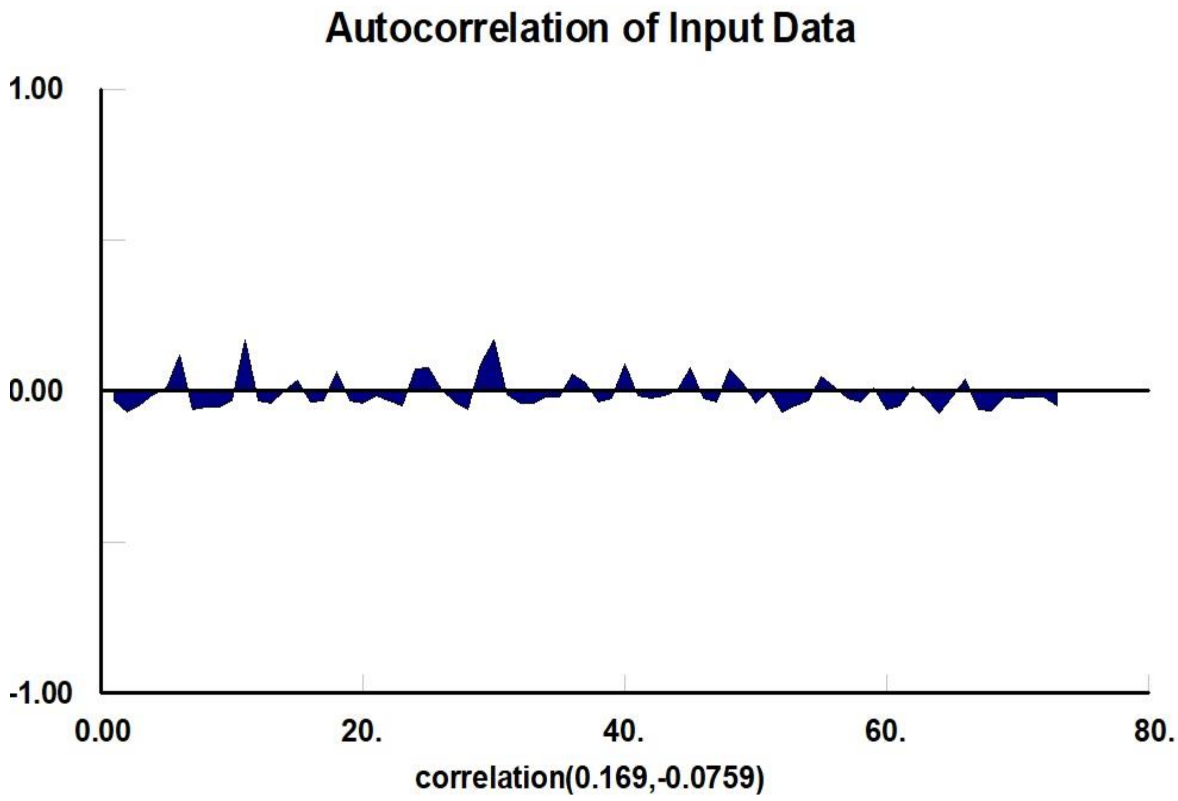

Figure A-11 Autocorrelation test on discharged BH crisis patient disposition-to-depart time

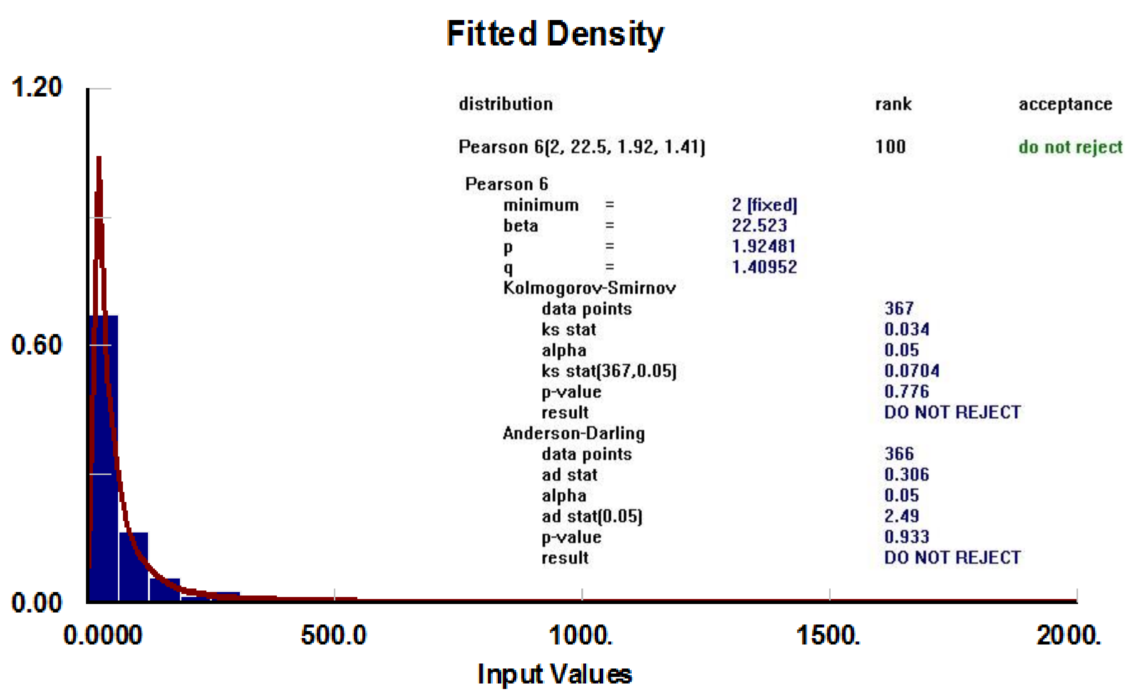

Figure A-12 Fitted distribution to discharged BH crisis patient disposition-to-depart time

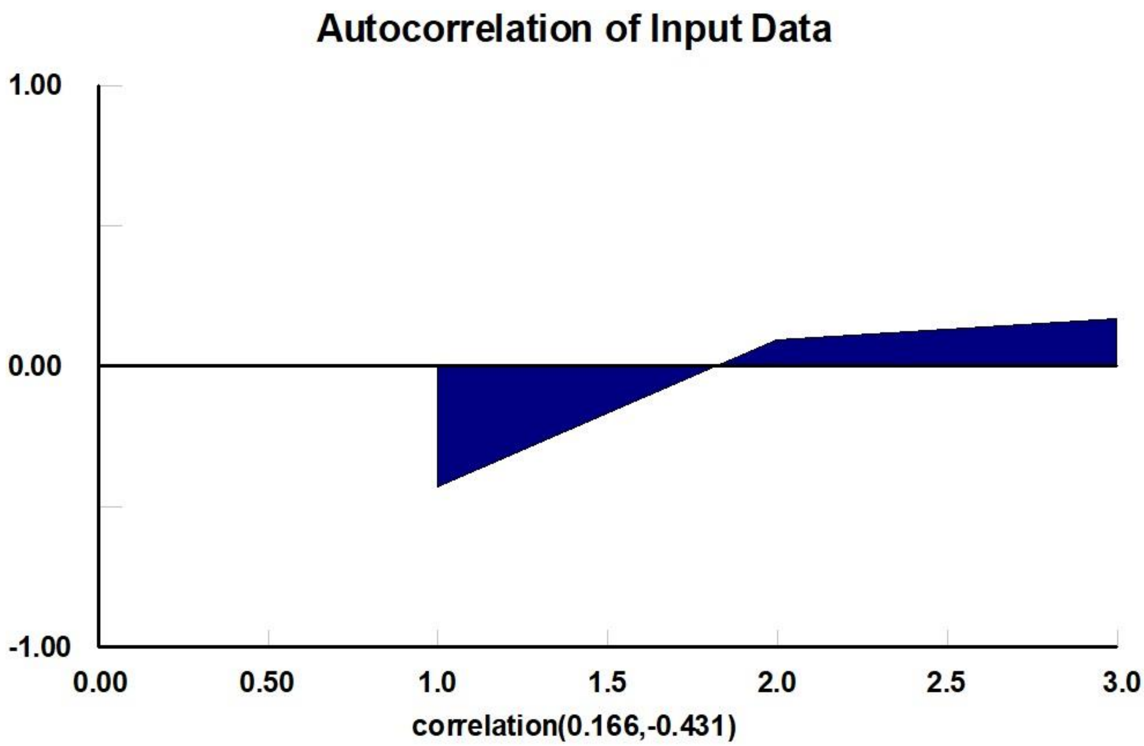

Figure A-13 Autocorrelation test on admitted/transferred regular patient roomed-to-disposition time (15 data points)

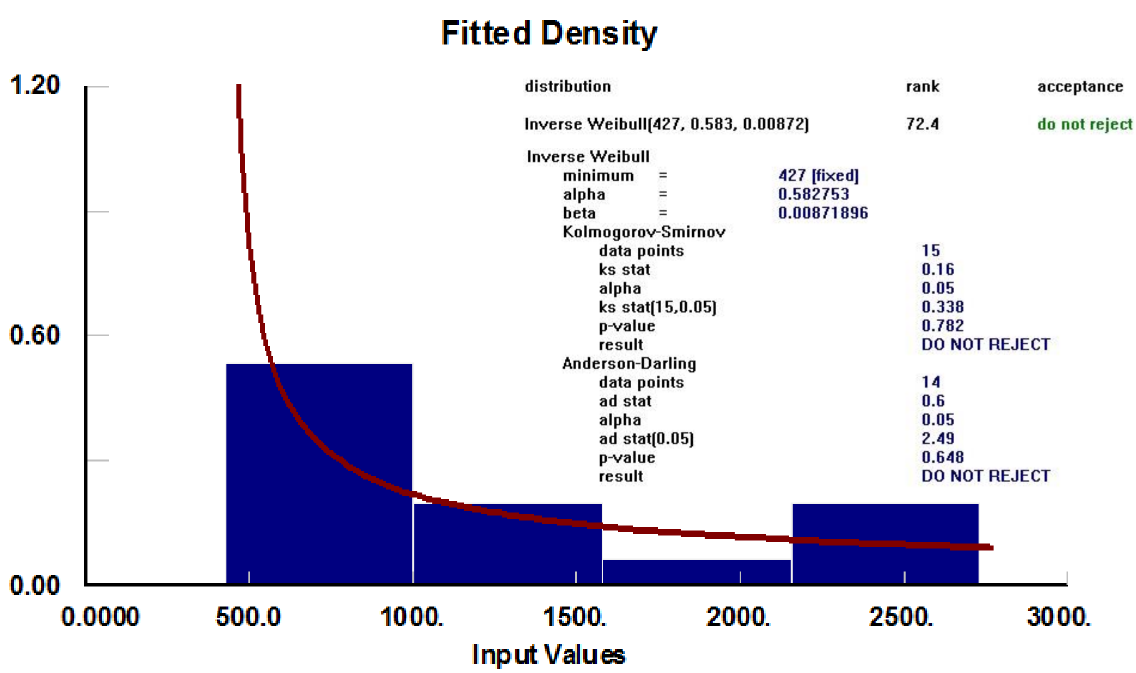

Figure A-14 Fitted distribution to admitted/transferred regular patients roomed-to-disposition time (15 data points)

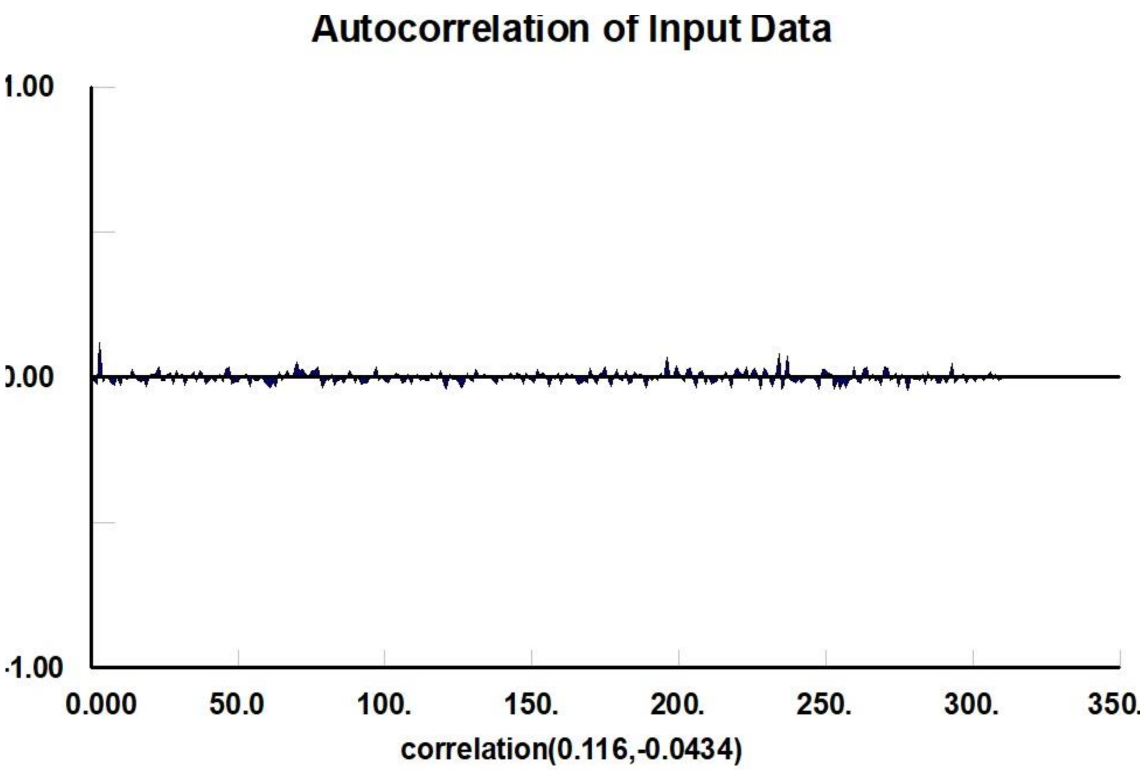

Figure A-15 Autocorrelation test on admitted/transferred regular patients roomed-to-disposition time (1538 data points)

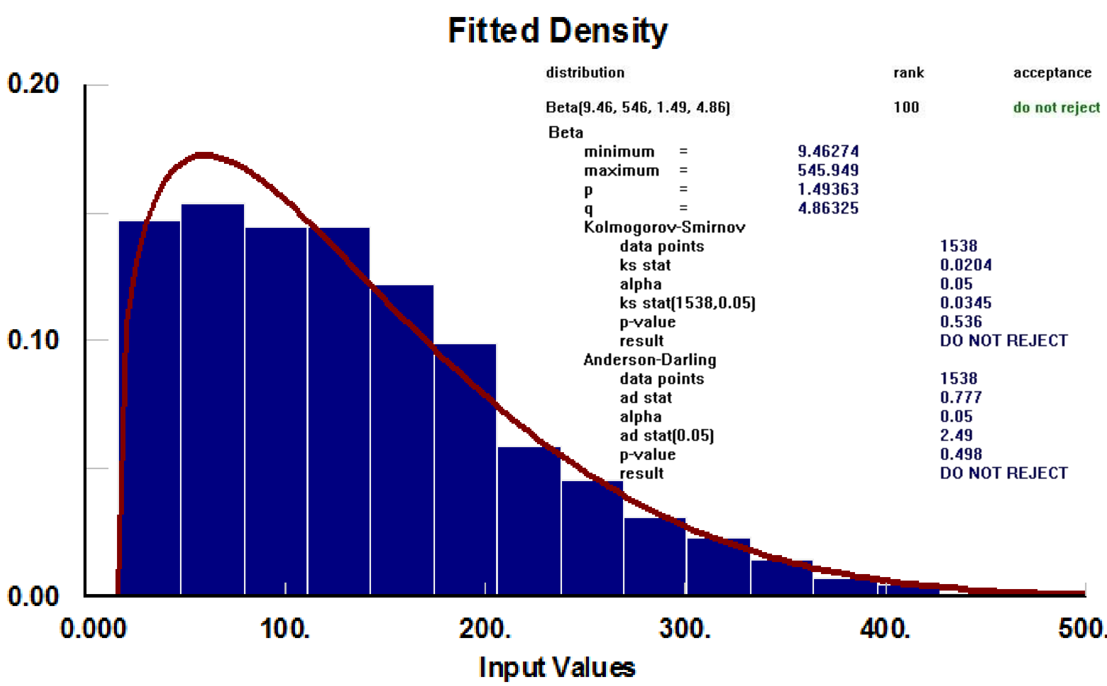

Figure A-16 Fitted distribution to admitted/transferred regular patients – roomed-to-disposition time (1538 data points)

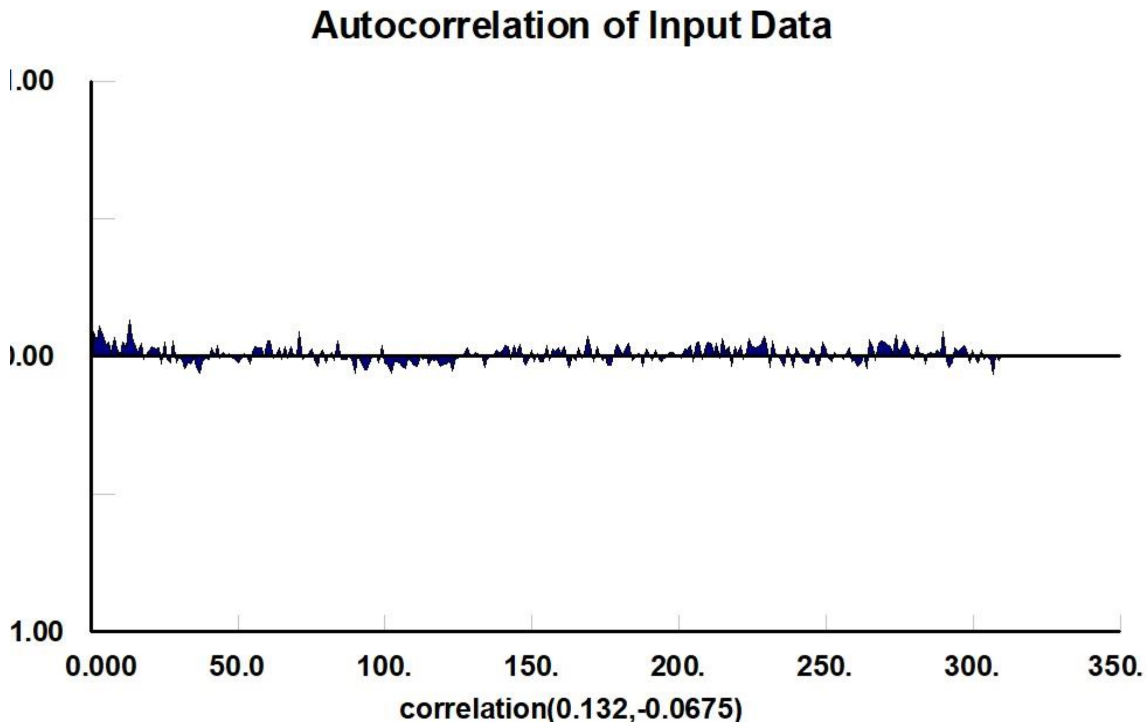

Figure A-18 autocorrelation test on admitted/transferred regular patient disposition-to-depart

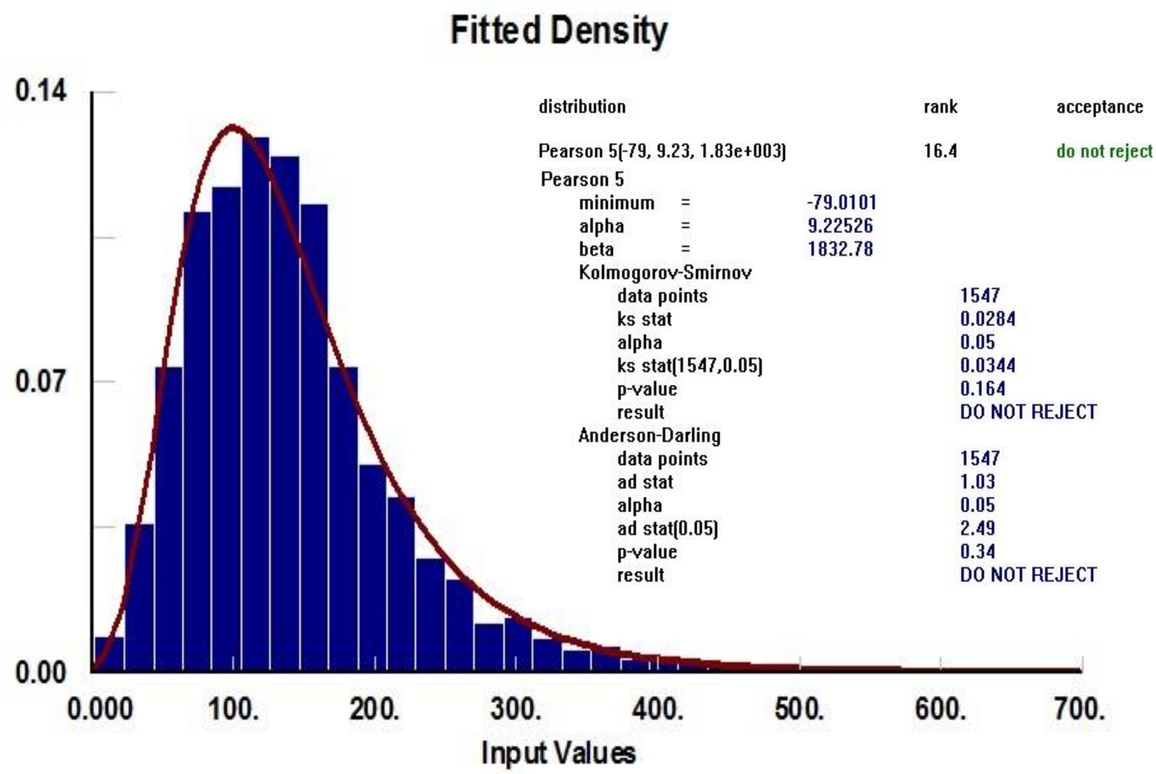

Figure A-17 Autocorrelation test on admitted/transferred regular patients disposition-to-depart time

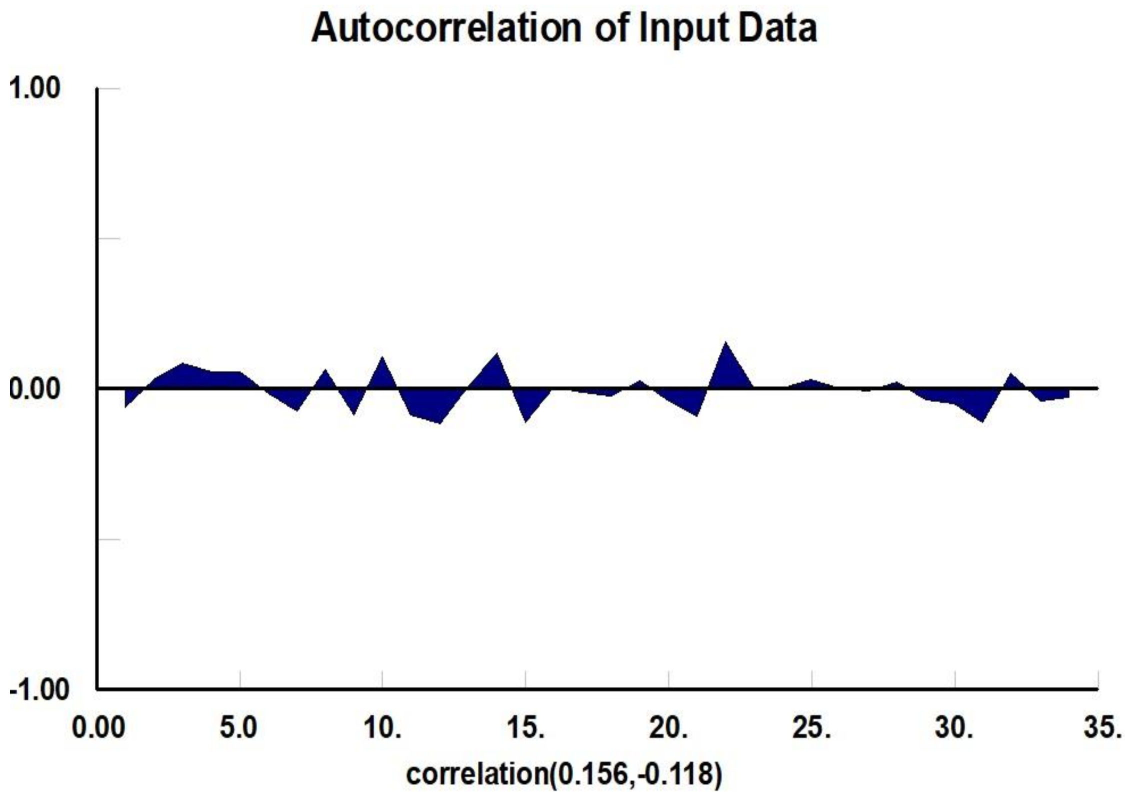

Figure A-19 Autocorrelation test on discharge regular patients roomed-to-disposition time (337 data points)

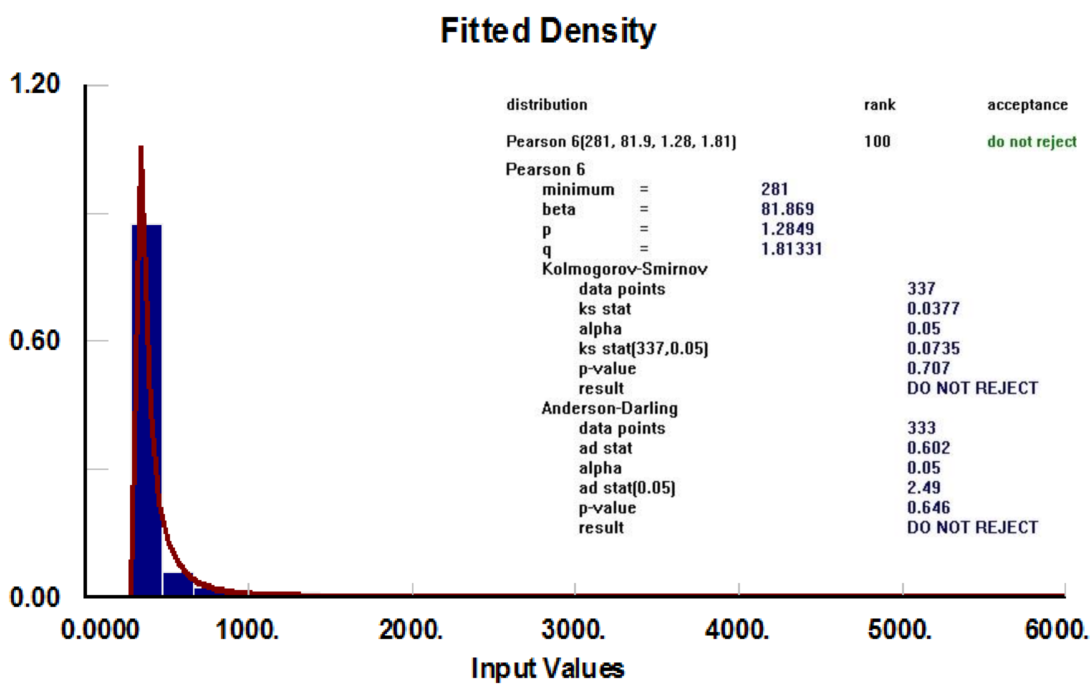

Figure A-20 Fitted distribution to discharged regular patients roomed-to-disposition time (337 data points)

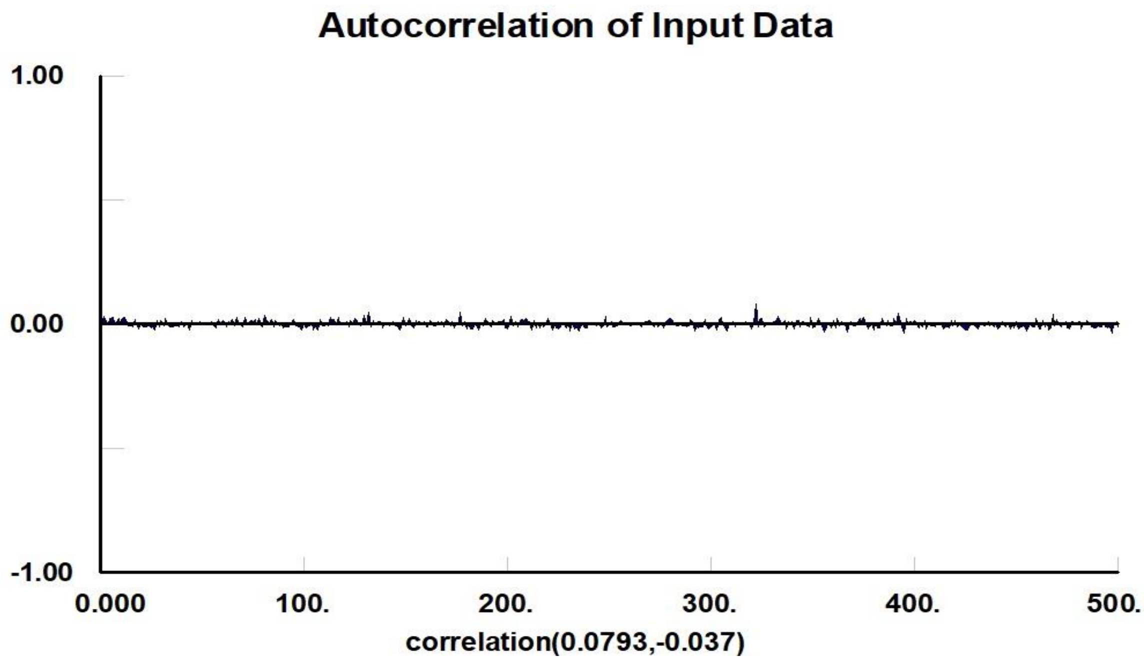

Figure A-21 Autocorrelation test on discharged regular patients roomed-to-disposition time (3275 data points)

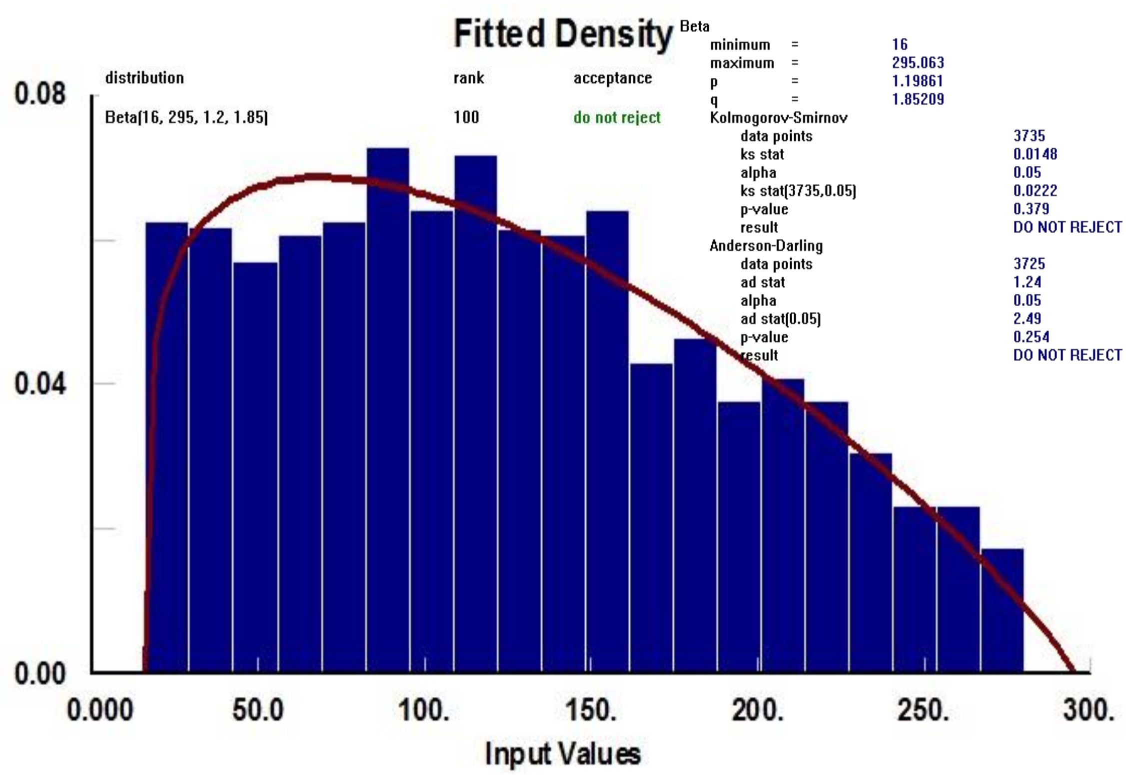

Figure A-22 Fitted distribution to discharged regular patients – roomed to disposition time (3725 data points)

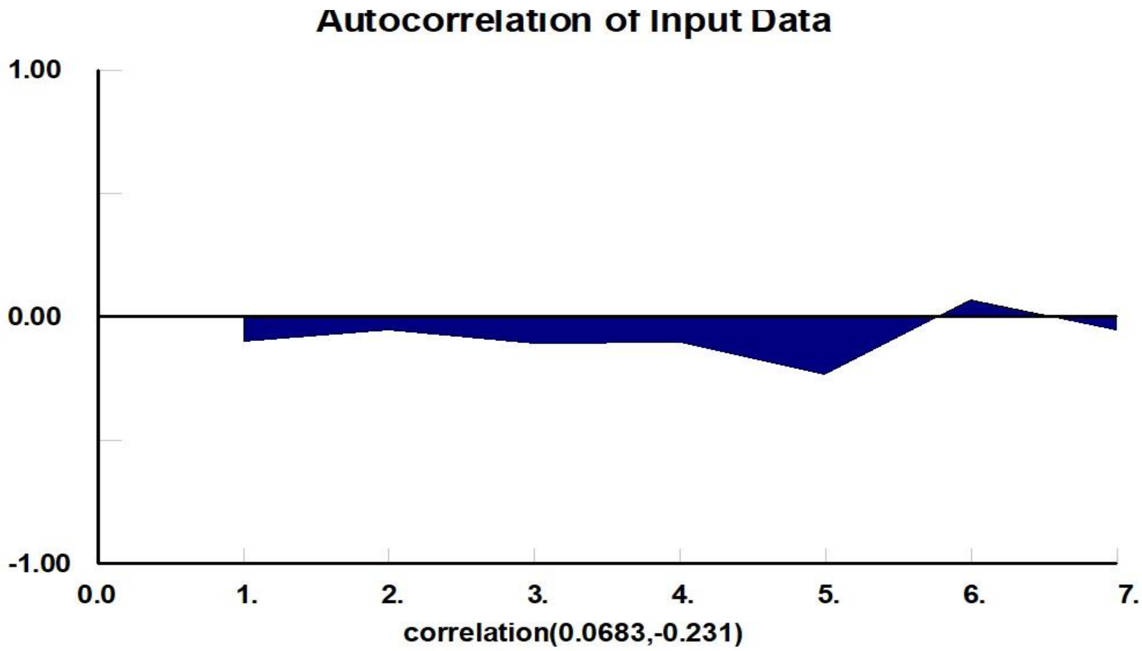

Figure A-23 Autocorrelation test on discharged regular patients disposition-to-depart time(38 data points)

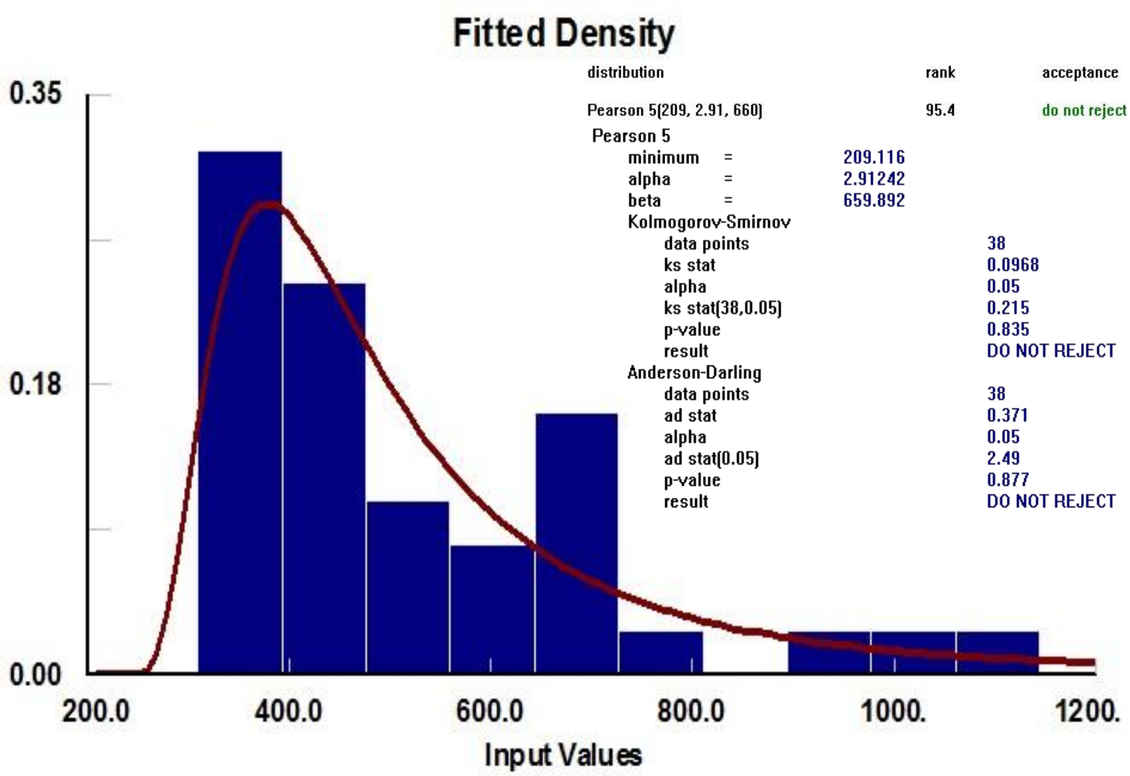

Figure A-24 Fitted distribution to discharged regular patients disposition-to-depart time (38 data points)

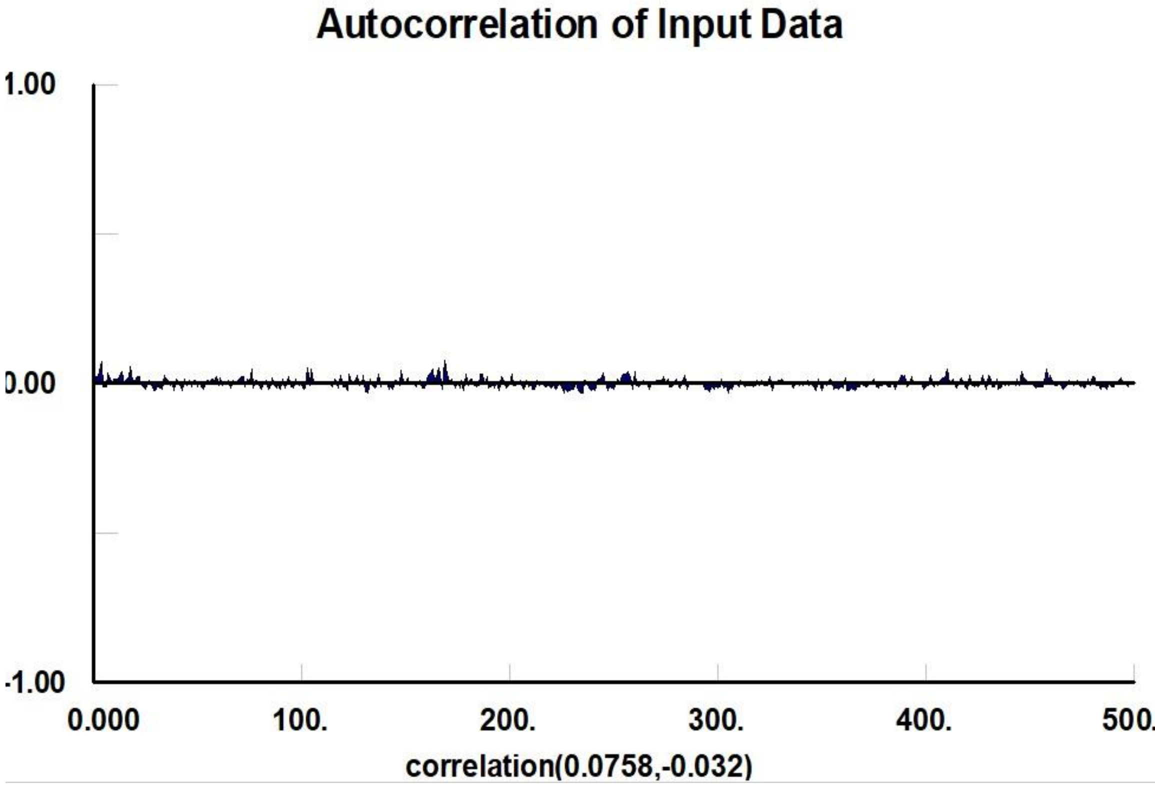

Figure A-25 Autocorrelation test on discharged regular patients disposition-to-depart time (4034 data points)

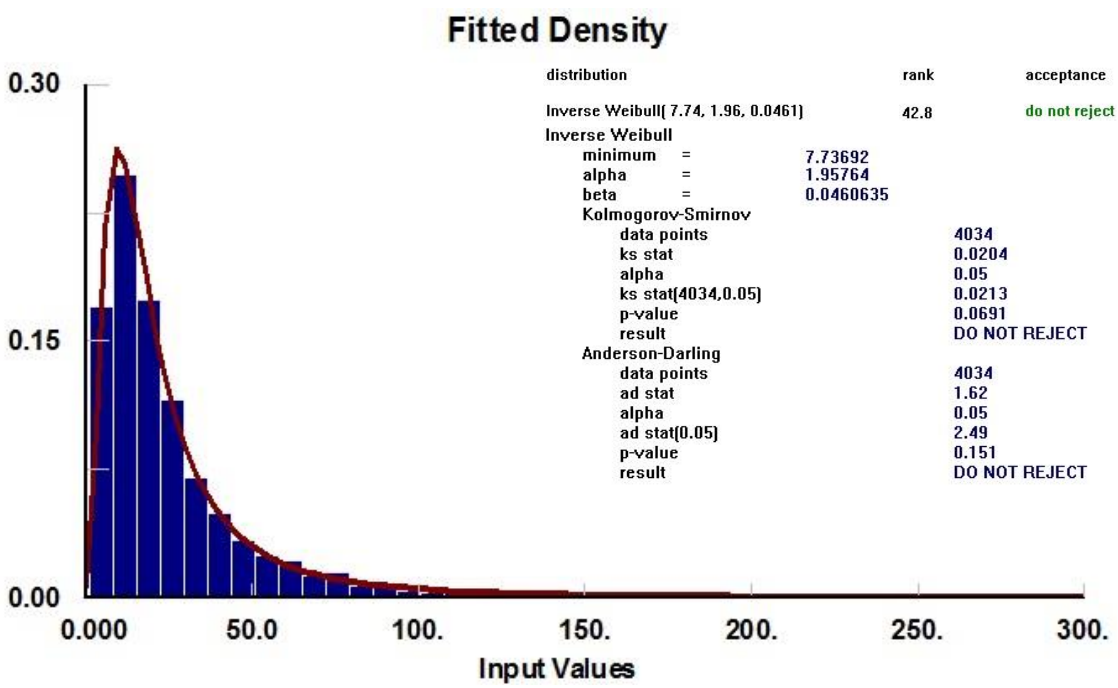

Figure A-26 Fitted distribution to discharged regular patients disposition to depart time (4034 data points)

B. Appendix 2

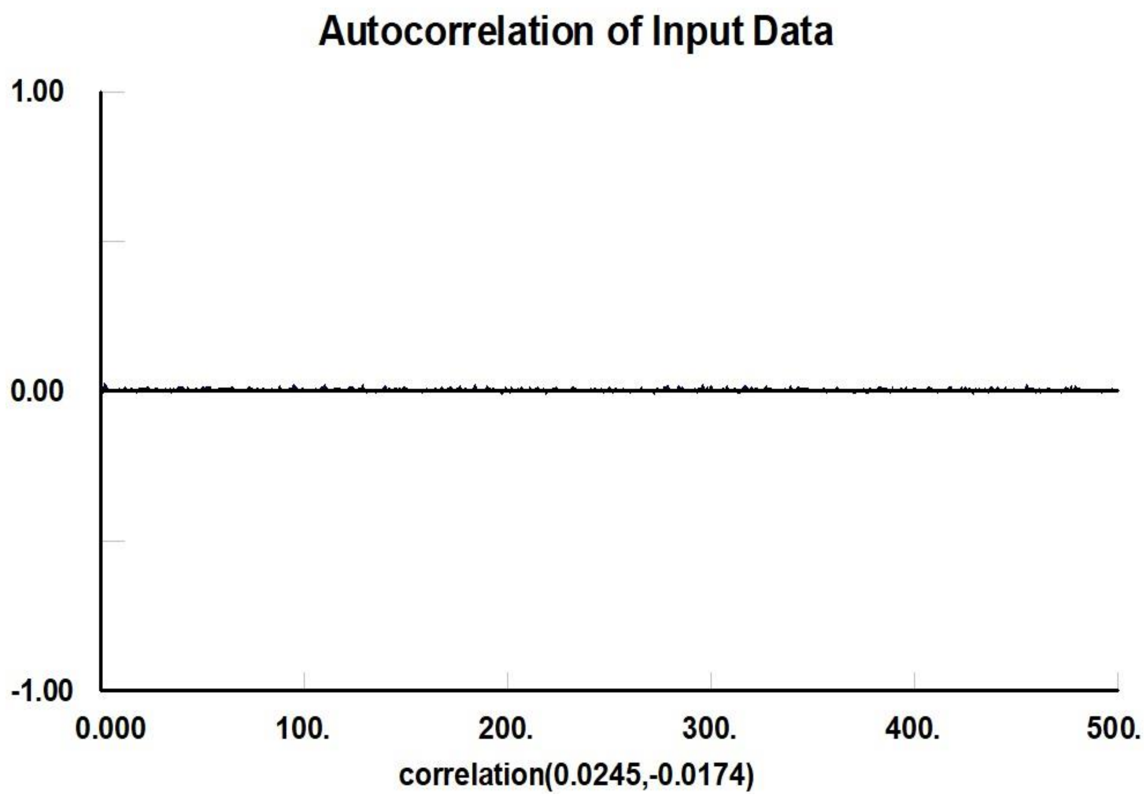

Figure B-1 Autocorrelation test on Lab ordered-to-collect time

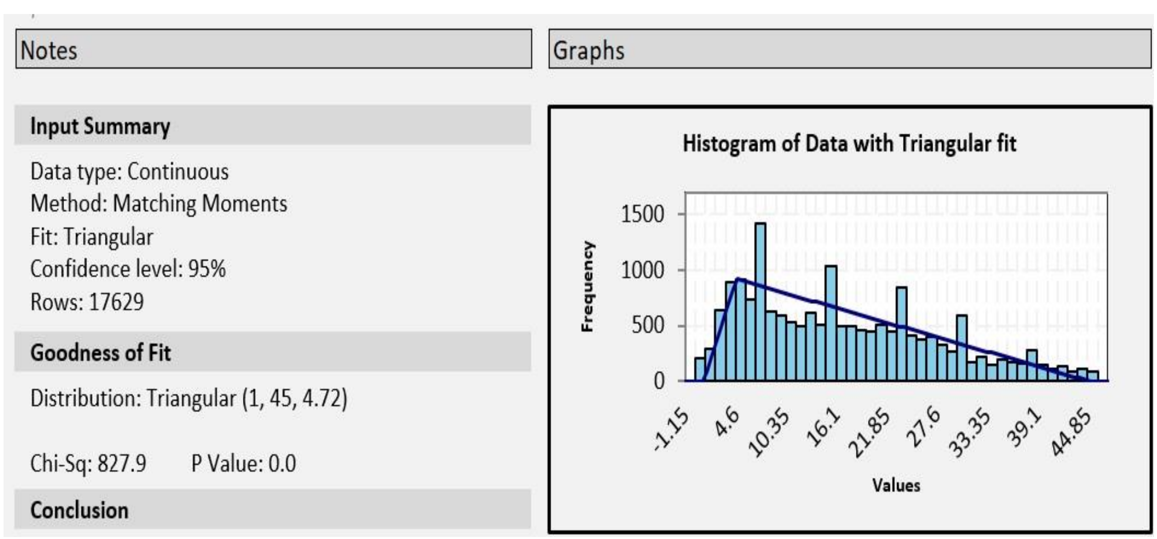

Figure B-2 Fitted distribution to lab ordered-to-collect time

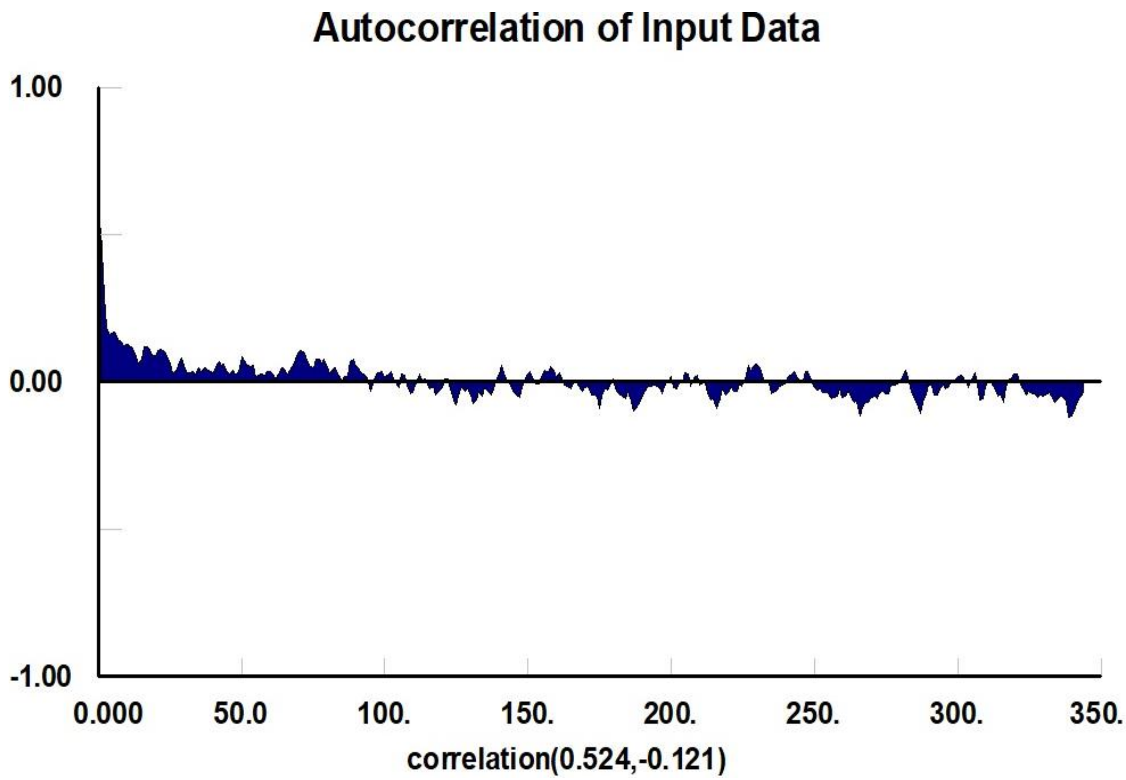

Figure B-3 Autocorrelation test on lab collected-to-receive time

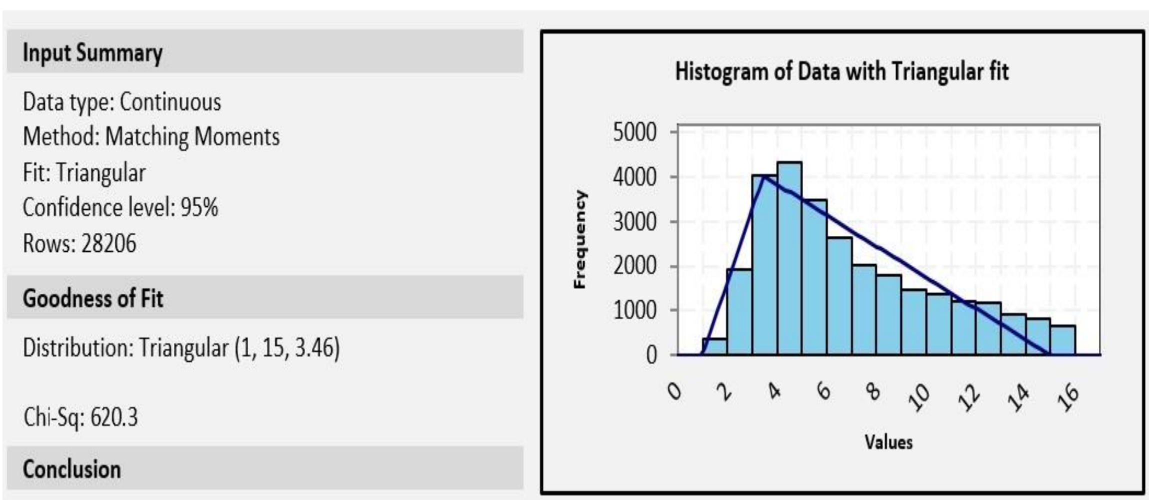

Figure B-4 Fitted distribution to lab collected-to-receive time

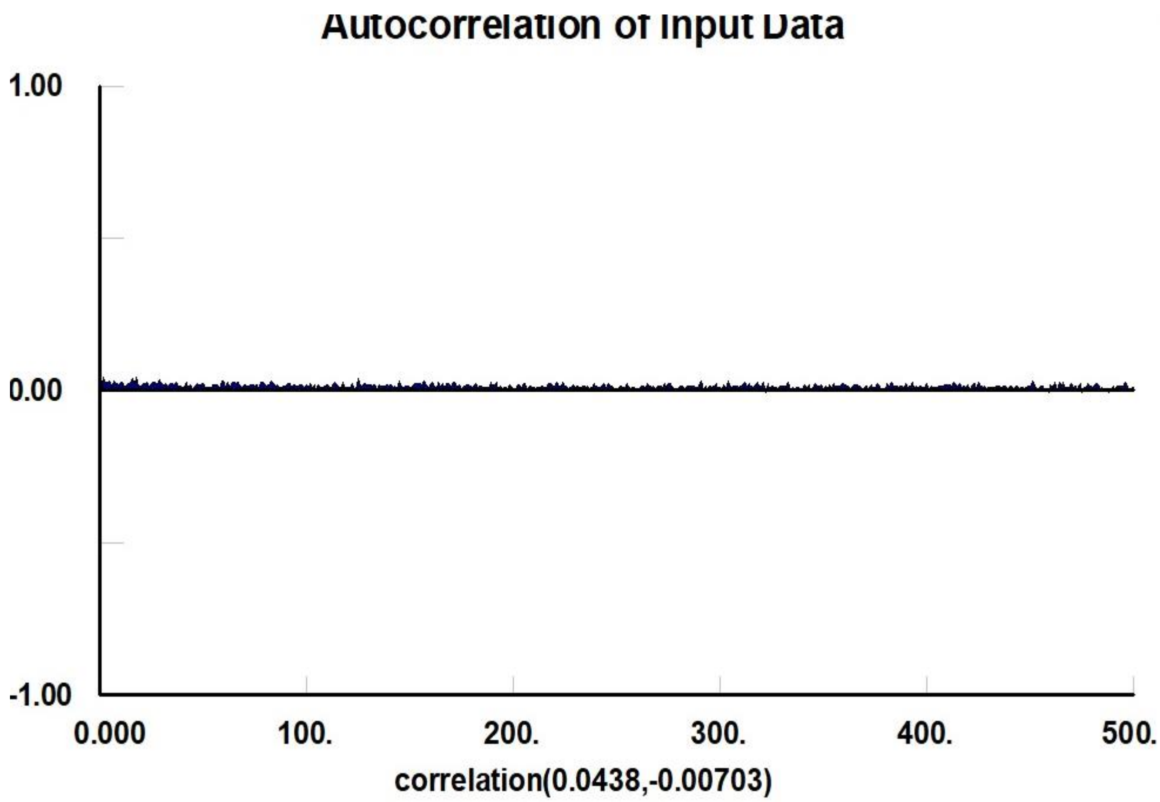

Figure B-5 Autocorrelation test on lab received-to-result time

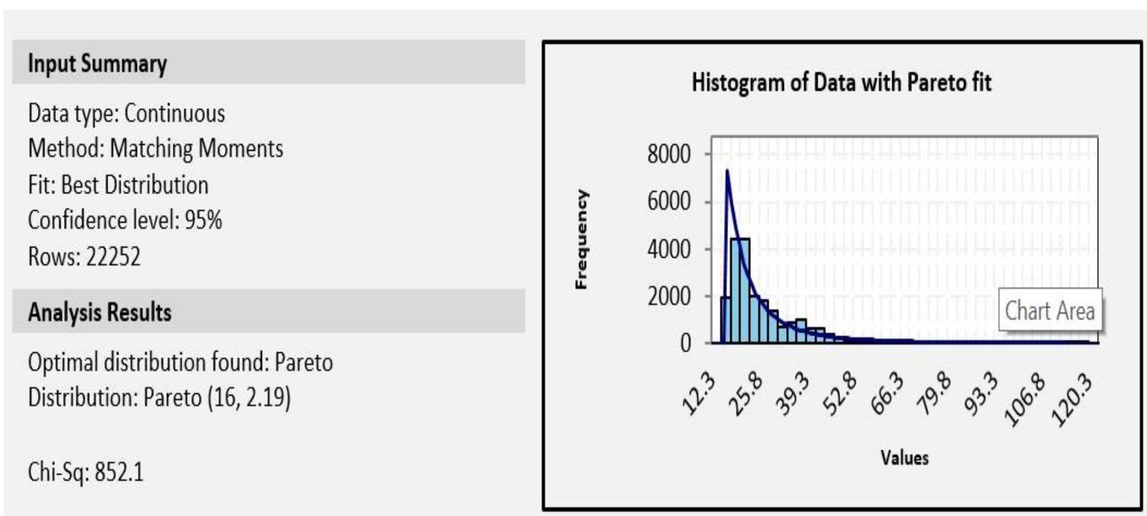

Figure B-6 Fitted distribution to Lab received-to-lab result time

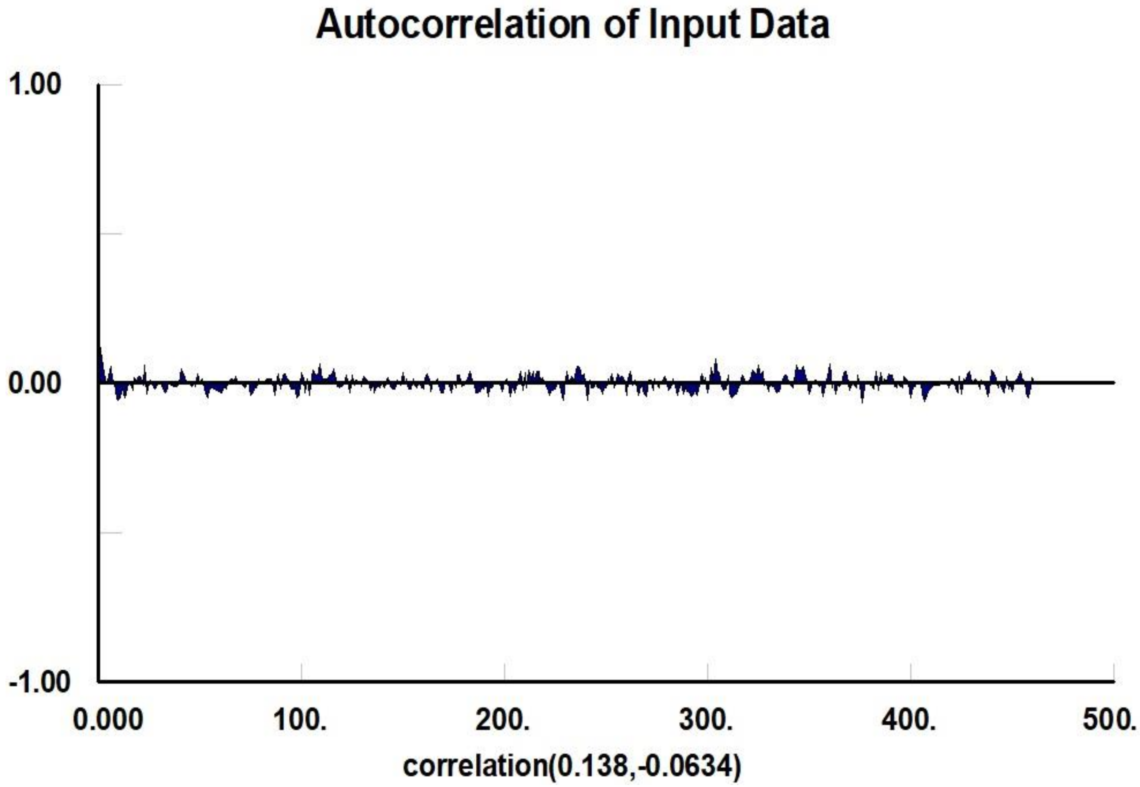

Figure B-7 Autocorrelation test on image ordered-to-exam-ended time

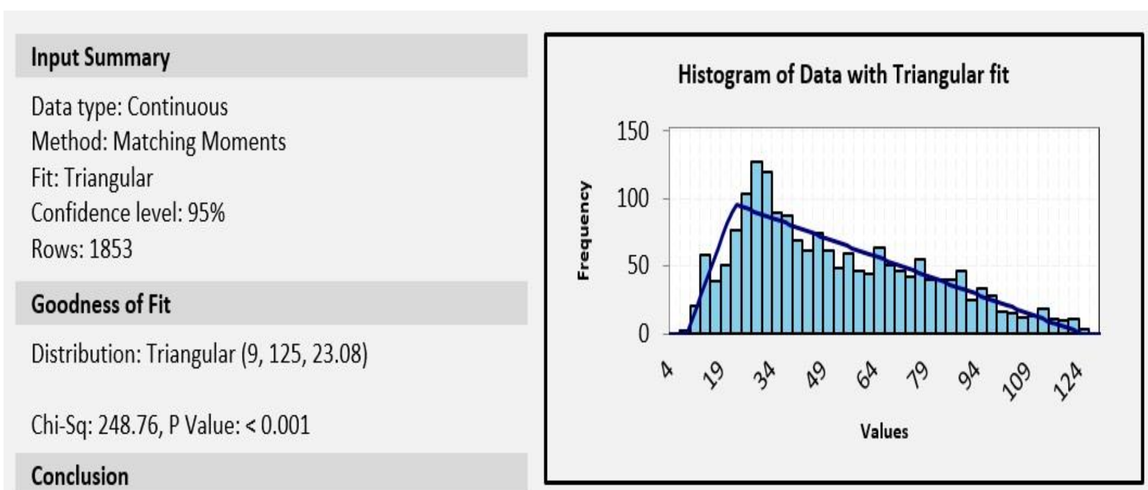

Figure B-8 Fitted distribution to Image ordered-to-exam-ended

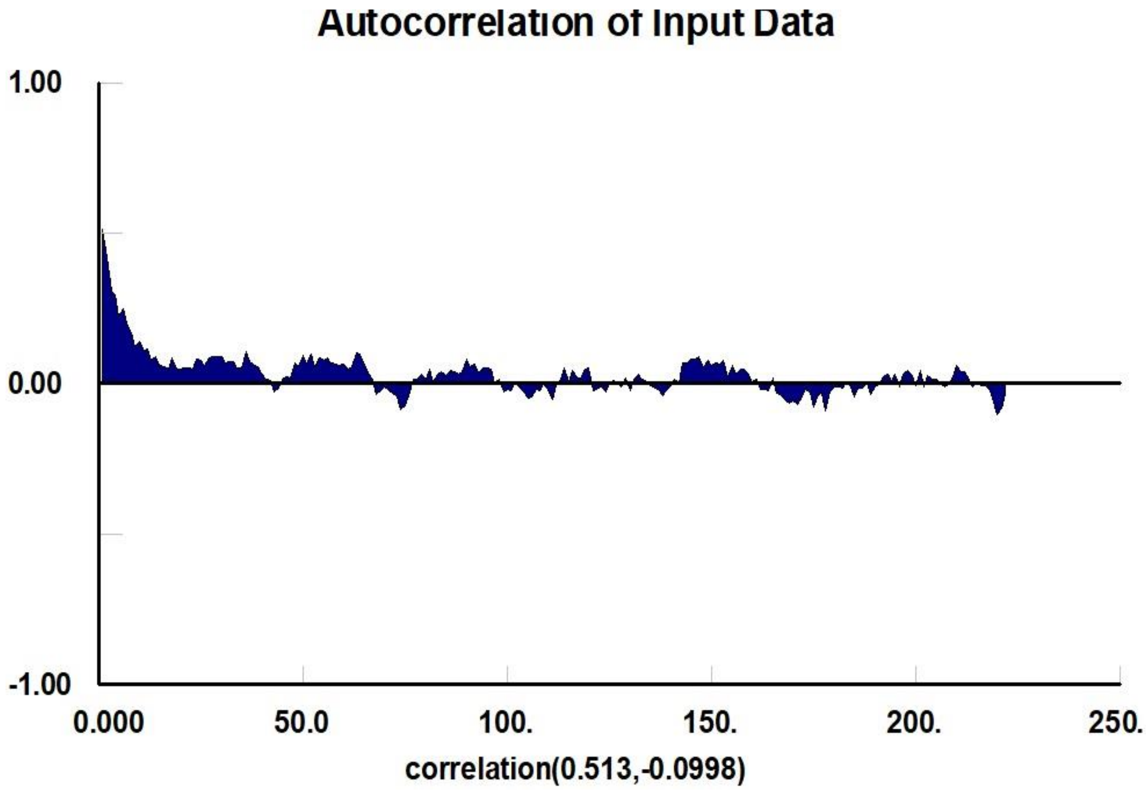

Figure B-9 Autocorrelation test on image exam-ended-to-result time

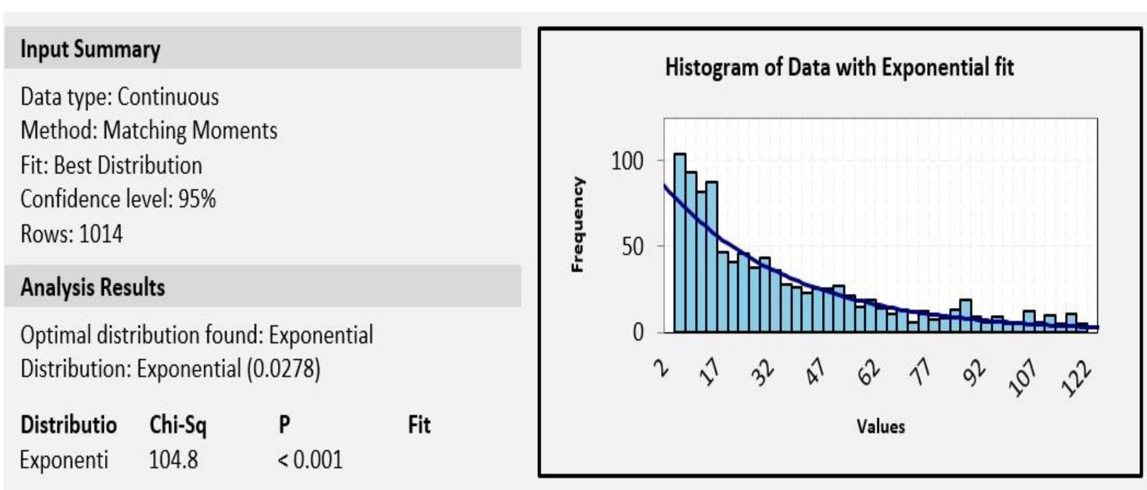

Figure B-10 Fitted distribution to Image exam ended-to-result

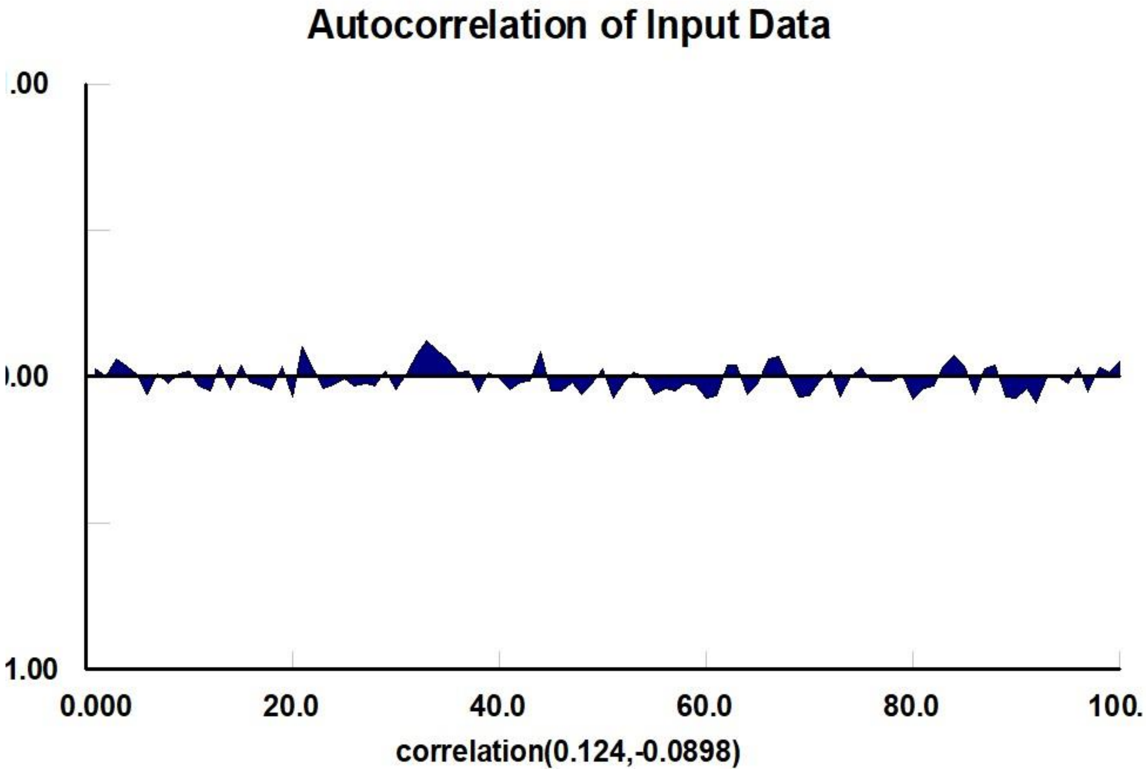

Figure B-11 Autocorrelation test on admitted/transferred BH crisis patients roomed-to-disposition time

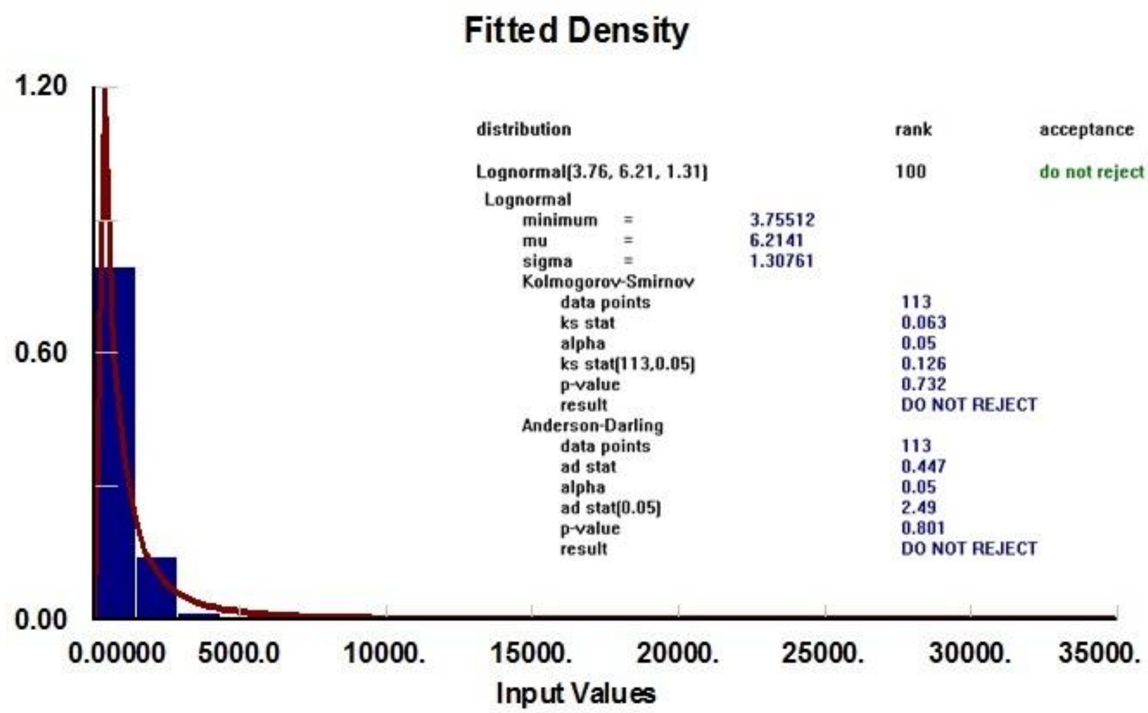

Figure B-12 Fitted distribution to admitted/transferred BH crisis patients roomed-to-disposition time

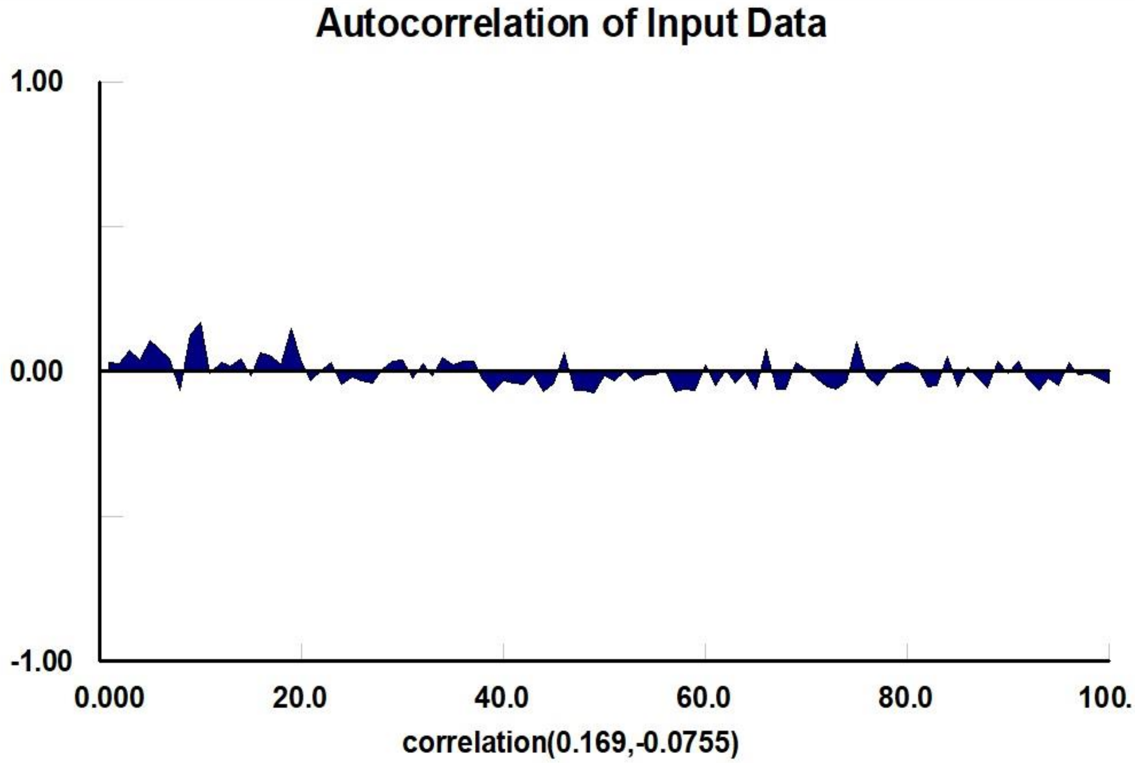

Figure B-13 Autocorrelation test on admitted/transferred BH crisis patients disposition-to-depart time

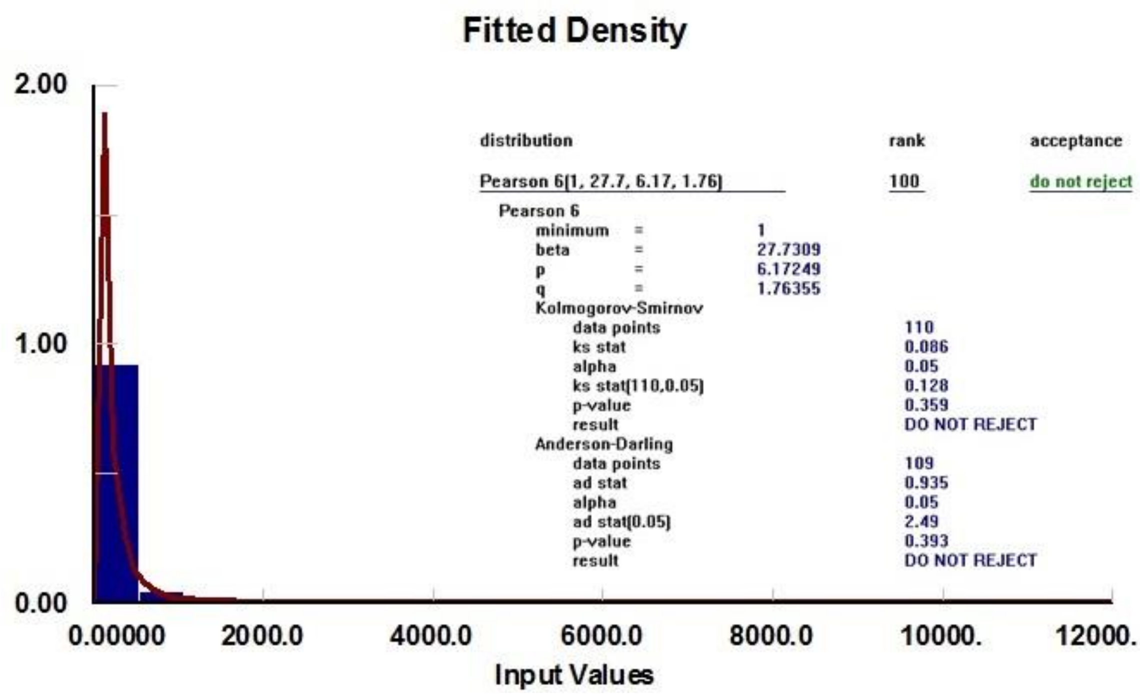

Figure B-14 Fitted distribution to admitted/transferred BH crisis patients disposition-to-depart time

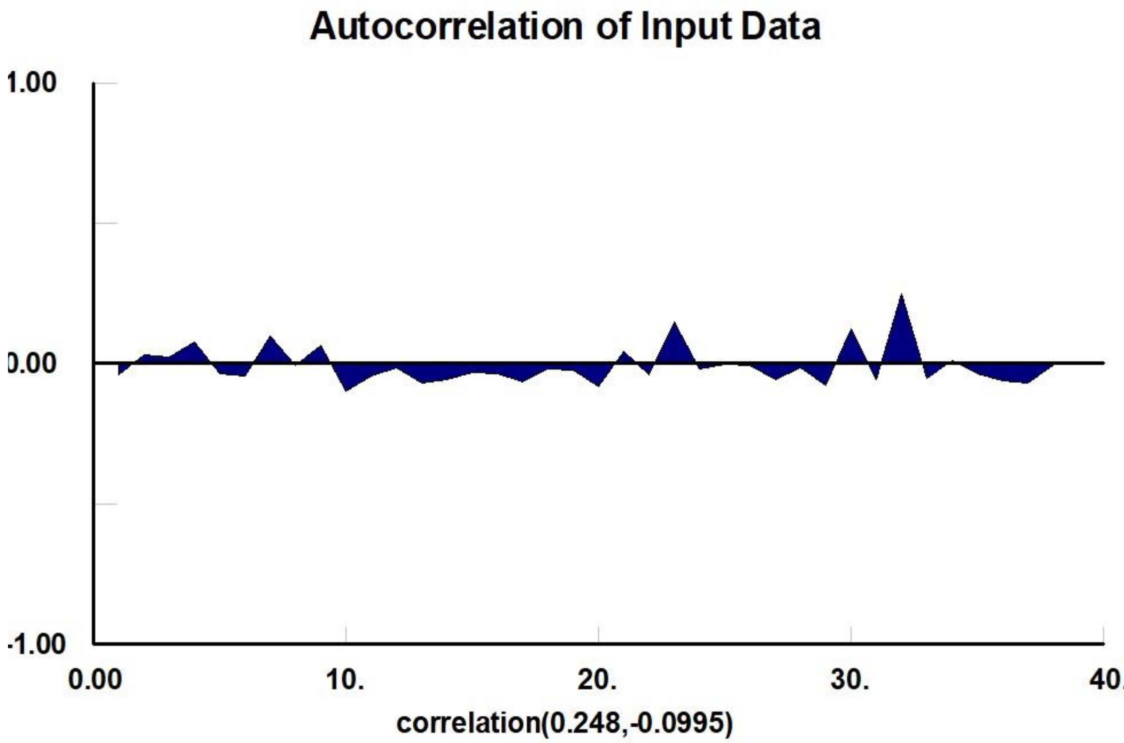

Figure B-15 Autocorrelation test on discharged BH crisis patients roomed-to-disposition time

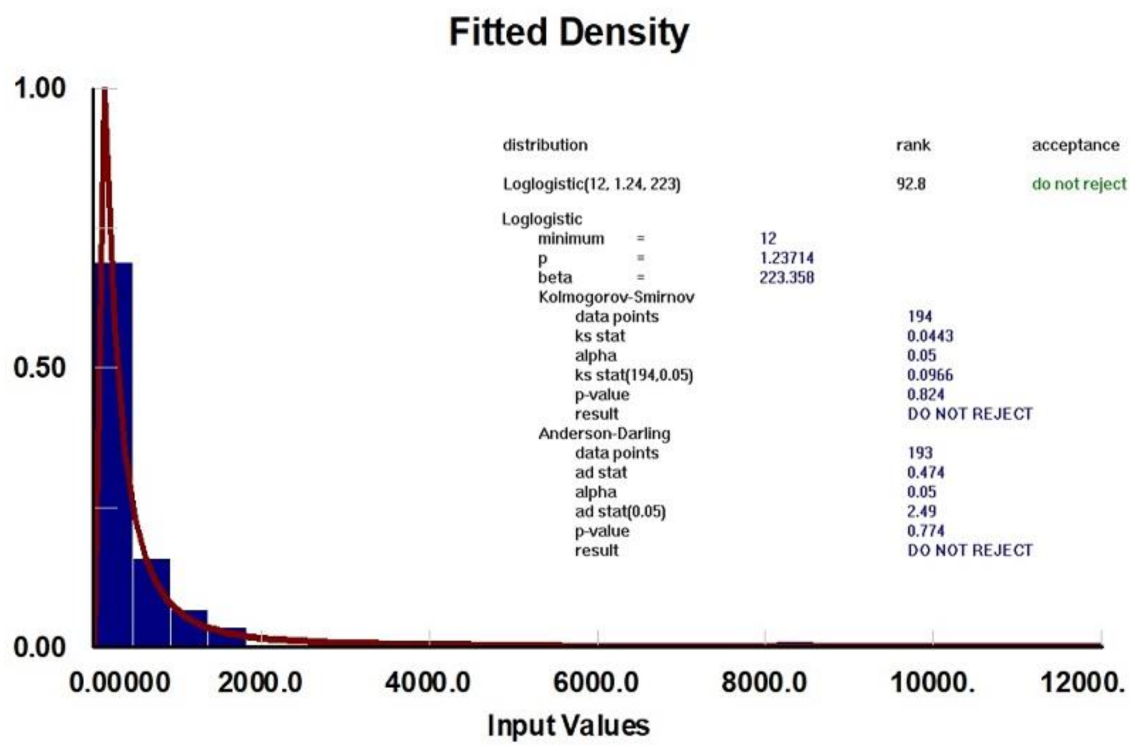

Figure B-16 Fitted distribution to discharged BH crisis patients roomed-to-disposition time

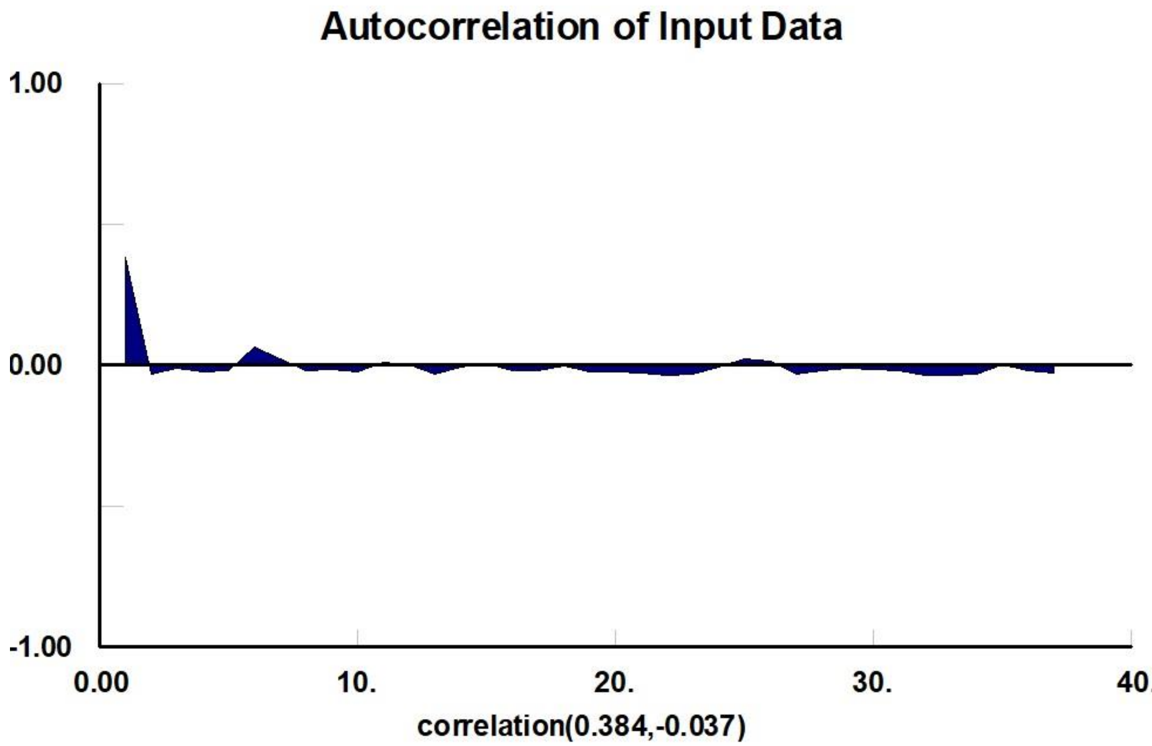

Figure B-17 Autocorrelation test on discharged BH crisis disposition-to-depart time

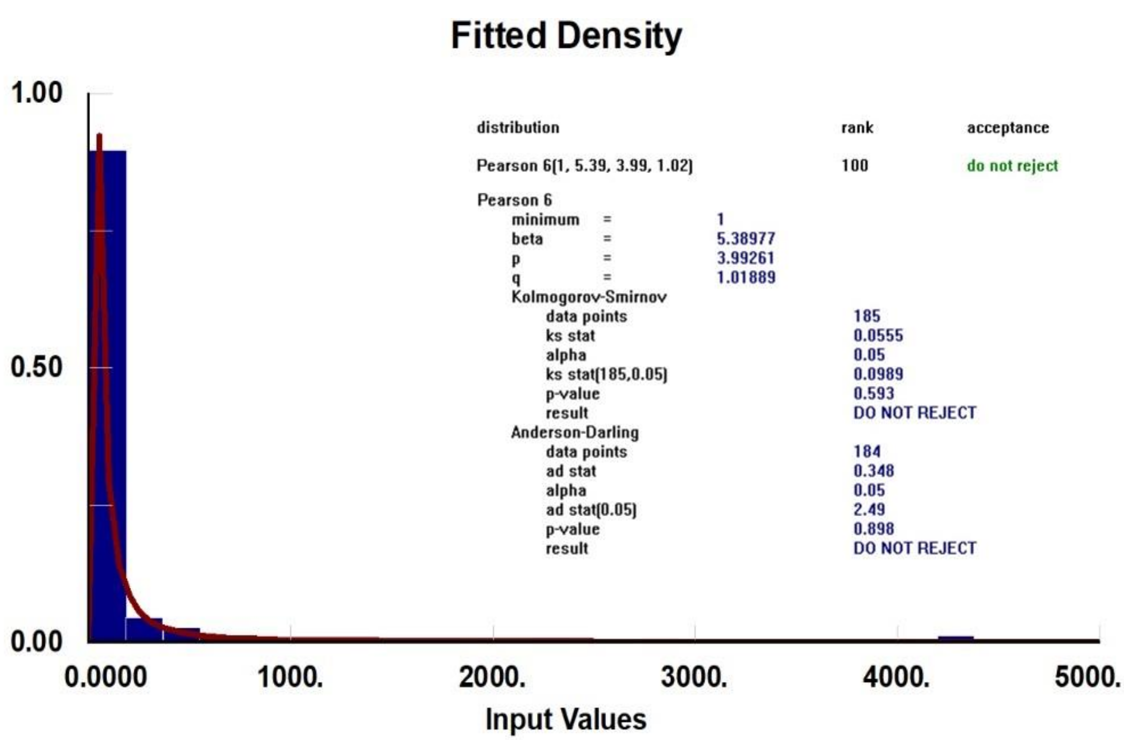

Figure B-18 Fitted distribution to discharged BH crisis disposition-to-depart time

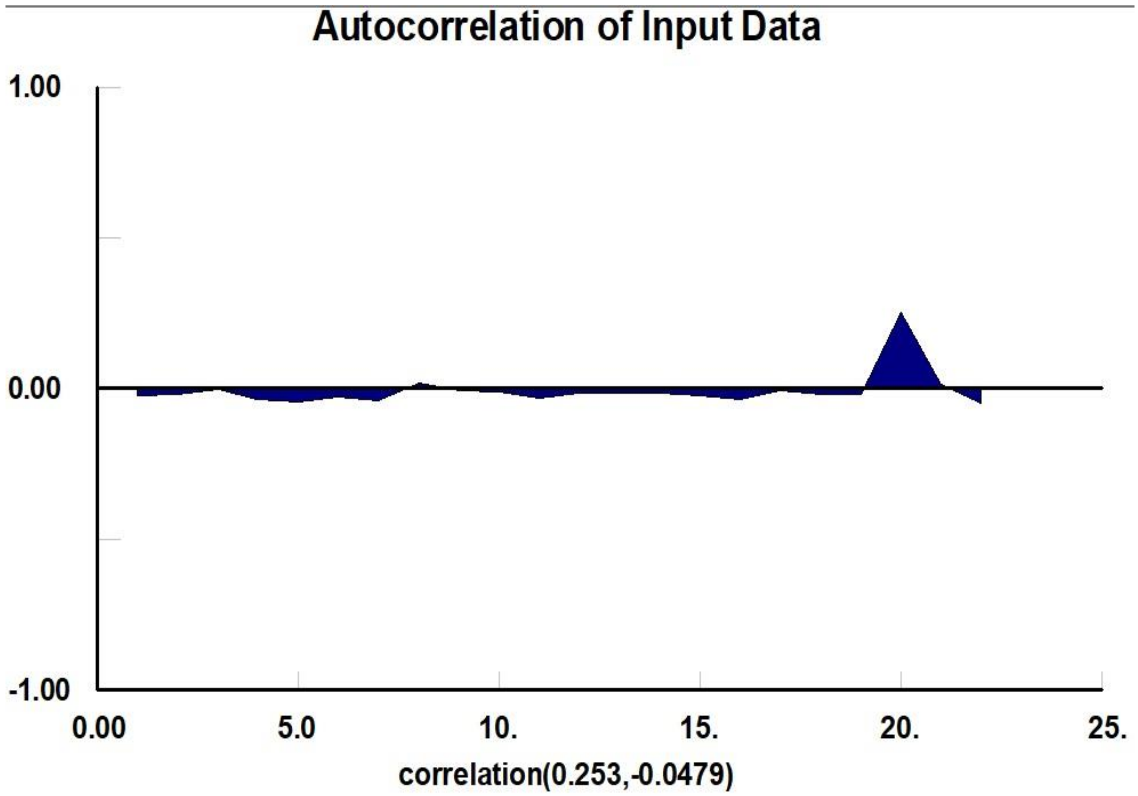

Figure B-19 Autocorrelation test on admitted/transferred regular patients disposition-to-depart time

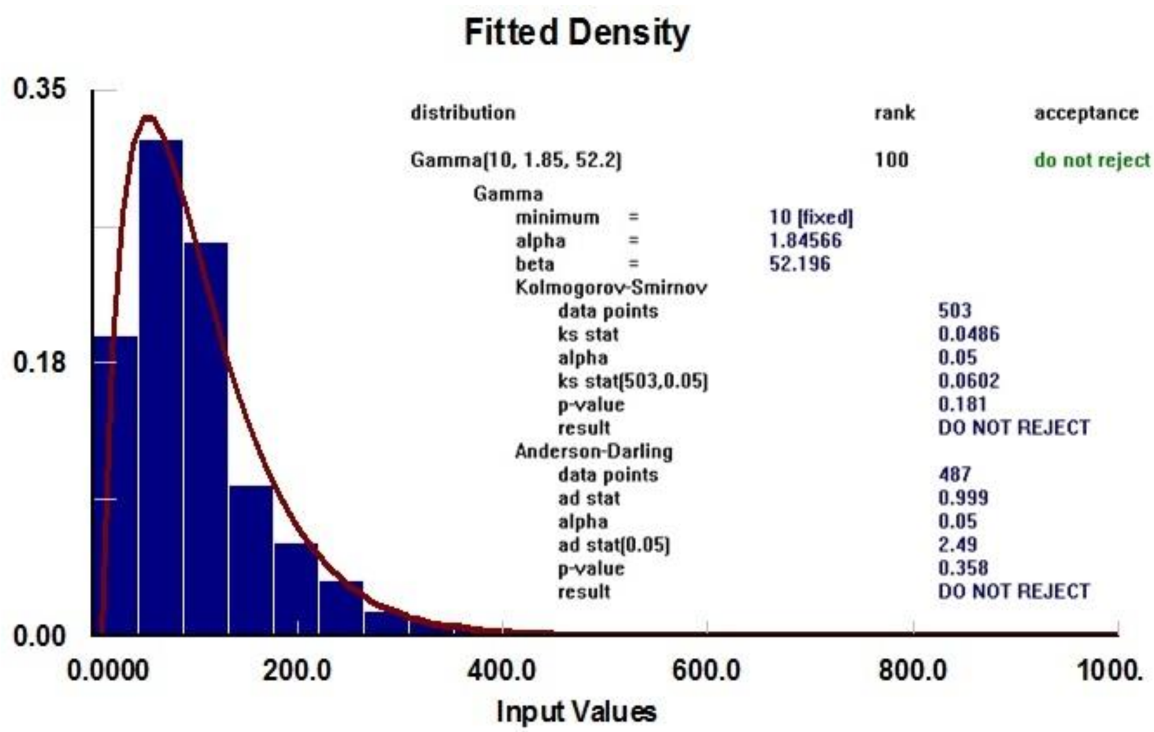

Figure B-20 Fitted distribution to admitted/transferred regular patients disposition-to-depart time

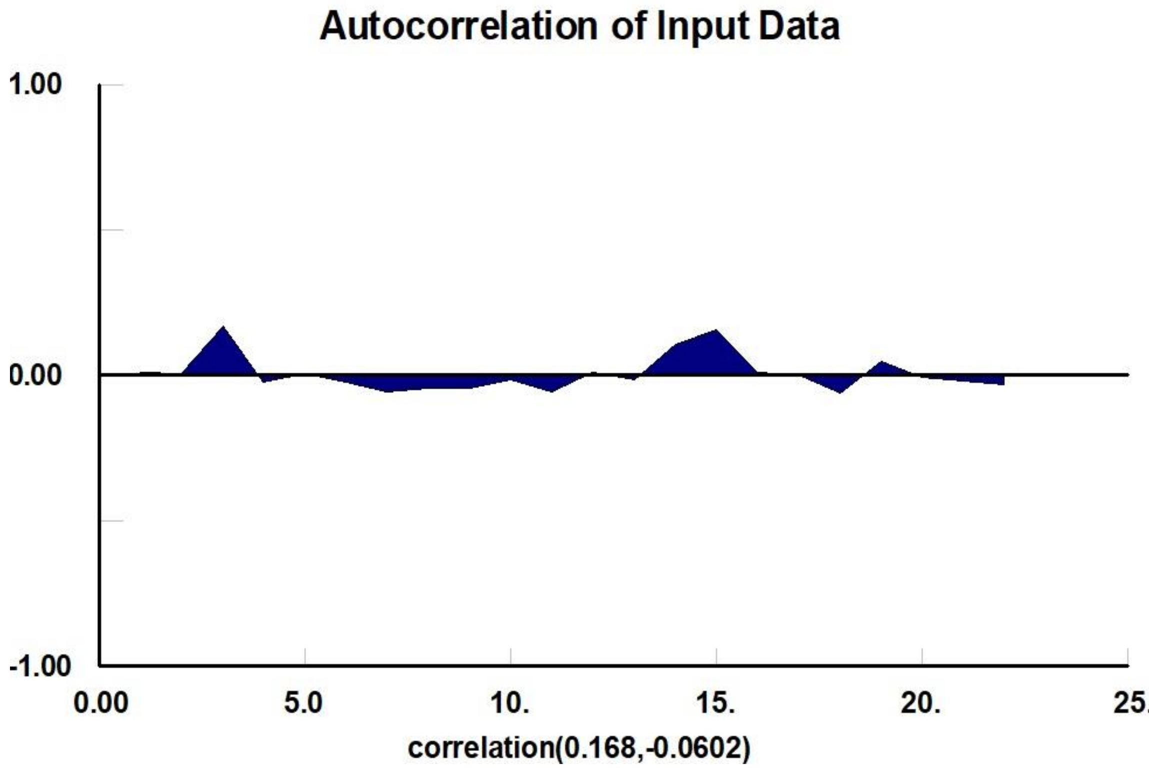

Figure B-21 Autocorrelation test on discharged regular patients disposition-to-depart time

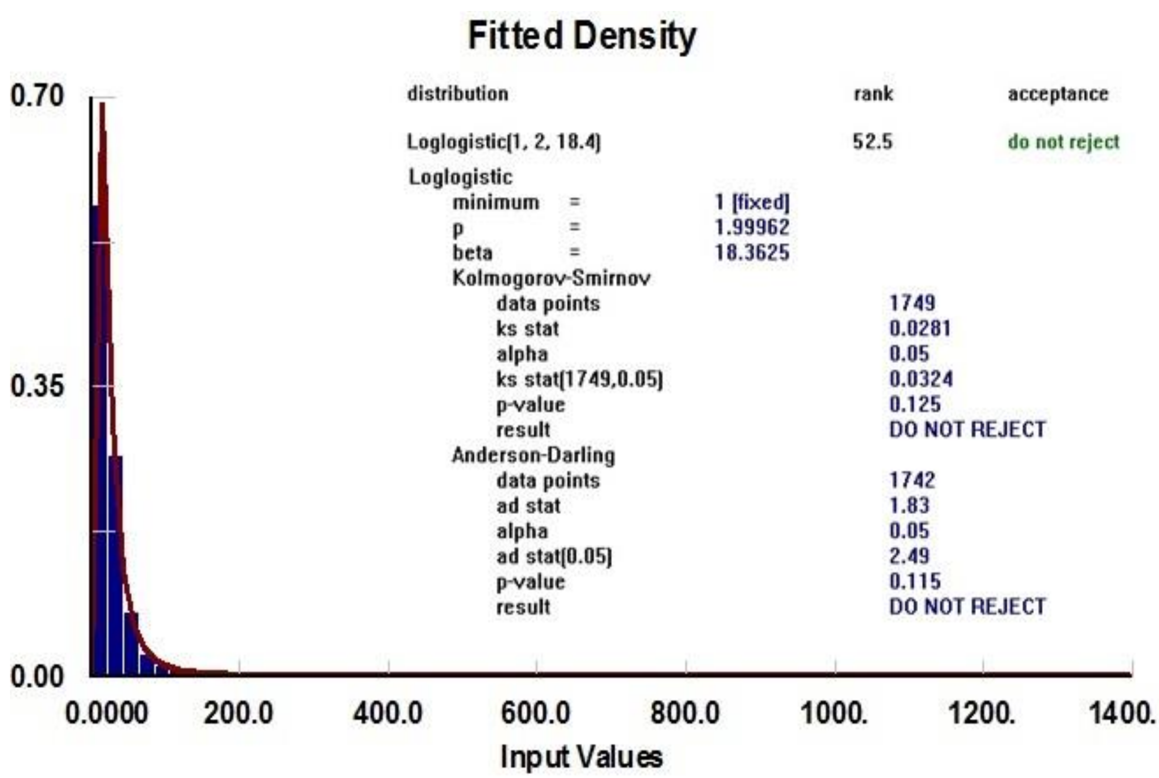

Figure B-22 Fitted distribution to discharged regular patients disposition-to-depart time